Reference-based transitions in short-run price elasticity

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Reference-based transitions in short-run price elasticity

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ABSTRACT

Marketing literature has long recognized that price response need not be monotonic and symmetric, but has yet to provide generalizable market-level insights on reference price type, asymmetric thresholds and sign and magnitude of elasticity transitions. In this paper, we introduce smooth transition models to study reference-based price response across 25 fast moving consumer good categories. Our application to 100 brands shows that 77% demonstrate reference-based price response, of which 36% reflects historical reference prices, 31% reflects competitive reference prices, and 33% reflects both types of reference prices. This reference-based price response shows asymmetry for gains versus losses on three levels: the threshold size, the sign and the magnitude of the elasticity difference. For historical reference prices, the threshold size is larger for gains (20%) than for losses (12%) and the assimilation/contrast effects for gains (-0.41) are smaller than the saturation effects for losses (0.81). For competitive reference prices, the threshold size is smaller for gains (3%) than for losses (16%), and the saturation effects are larger for gains (0.33) than for losses (0.15). These results are moderated by both brand and category characteristics that affect reference price accessibility and diagnosticity. Historical reference prices more often play a role for national brands, for planned purchases and in inexpensive categories with low price volatility and high purchase frequency. When price discounting, high-share brands face larger latitudes of acceptance. When raising prices, saturation effects set in later for brands with high price volatility and for categories with high price spread and for planned purchases. As for competitive reference prices, saturation effects set in later for expensive brands with high price volatility and in categories with lower price volatility, higher price spread and higher concentration. Sales, revenue and margin implications are illustrated for price changes typically observed in consumer markets.

Keywords: kinked demand curve, smooth-transition regression models, competitive versus historical reference prices, asymmetric price thresholds, saturation versus assimilation/contrast effects, empirical generalizations.

1. INTRODUCTION

Marketing researchers and practitioners have long acknowledged that price response functions need not be monotonic and symmetric (e.g. Gabor and Granger 1964; Monroe 1990). In particular, the reference price concept puts a uniquely marketing spin on the traditional economics perspective by asserting that consumers respond to both actual and perceived prices (Kalyanaram and Winer 1995), producing kinked demand curves (Putler 1992). Managerial interest in such kinked demand curves is twofold: (1) predicting the sales and profit impact of different levels of price increases and decreases and (2) identifying the brand and category characteristics that impact these thresholds (Han, Gupta and Lehmann 2001). Indeed, in-depth interviews reveal that managers "want to know where the thresholds points lie so they can fine-tune price setting" (Bucklin and Gupta 1999, p.250). As managers typically assess threshold effects by simple methods based on a cross-tabulation of sales versus price points across stores, Bucklin and Gupta (1999) call for more academic research on price threshold analysis.

From a research perspective, there have been two sophisticated approaches to the problem of estimating price thresholds. First, individual-level analyses showed asymmetric thresholds around a reference price, but remained restricted to the specific behavioral phenomenon of interest: historical versus competitive reference prices, assimilation/contrast effects versus saturation effects (Gupta and Cooper 1992; Thaler 1985). Second, completely data-driven approximation of the effect curve offered more flexible estimation approaches, at the expense of excessive data requirements and difficult interpretation of the parameters, especially across categories (Van Heerde et al. 2001; Kalyanam and Shively 1998).

The first stream of research, based on individual-level data, models thresholds explicitly based on the notion that individuals have reference prices against which they evaluate current prices when making a choice. Two main issues in this research stream are the nature of this reference price and the asymmetry of thresholds for gains i.e. price reductions, versus losses i.e. price increases (Kalyanaram and Winer 1995; Han et al. 2001). First, empirical researchers have typically assumed that consumers use either a historical (temporal) reference price (hereafter HRP) or a competitive (contextual) reference price (hereafter CRP) in brand choice decisions (Klein and Oglethrope 1987; Briesch, Krishnamurthi, Mazumdar and Raj 1997). The former view argues that consumers remember the prices encountered on past purchase occasions while the latter view argues that a reference price is formed during the purchase occasion on the basis of the prices observed (e.g. shelf prices of competing products). This distinction in reference price formation is important for market-level price setting. Historical reference prices imply that managers should beware of own past discounting as brand price should compare favorably with past own prices, whereas competitive reference prices focus management attention on current competitive prices as brand price should compare favorably with those at the point of purchase (Mazumdar and Papatla 2000; Rajendran and Tellis 1994). Interestingly, the few papers that analyzed both historical and competitive reference prices (in one or a few product categories) find that both reference types matter (Kumar, Karande and Reinartz 1998; Mayhew and Winer 1992; Rajendran and Tellis 1994 and Mazumdar and Papatla 2000). Unfortunately, however, this finding yields few managerial guidelines as to the circumstances under which each type is more important, in the absence of a large-scale investigation on the relative importance of historical (temporal) versus competitive (contextual) reference price.

Second, researchers have identified thresholds in price response across the reference point (Kalyanaram and Little 1994; Raman and Bass 2002) and have called for further exploration of this issue (Bucklin and Gupta 1999; Kalyanaram and Winer 1995). In particular, the thresholds could be asymmetric to gains (price decreases) versus losses (price increases) and may depend on brand and category characteristics (Krishnamurthi, Mazumdar and Raj 1992; Kalyanaram and Little 1994). Recently, Han et al. (2001) find evidence of asymmetric thresholds for gains (larger) versus losses (smaller) in the coffee category and relate these to three moderating variables. To the best of our knowledge however, no paper has modeled both historical and competitive reference prices while allowing for asymmetric thresholds at the same time.

In constrast to the first stream of research, a second research stream allows for a completely data-driven approximation of the effect curve to capture non-constant effects, such as the semi-parametric approach in Van Heerde et al. (2001) or the stochastic spline-regression approach in Kalyanam and Shively (1998). The latter uses Bayesian methods and Gibbs sampling in conjunction with spline regression to estimate irregular price response function on aggregate-level data. These approaches are extremely flexible, thereby reducing the possibility of model mis-specification bias. For instance, the semi-parametric model led to the discovery of saturation effects (Van Heerde et al. 2001), the phenomenon that price elasticity is reduced at some distance from the reference point. Unfortunately, the data requirements of such models quickly become excessive, and their parameters are hard to directly interpret. Indeed, to detect the location of e.g. threshold or saturation levels, the researcher either needs to perform a subjective eye-balling of the semi-parametric effect curve, followed by an allocation to a discrete interval (e.g. Van Heerde 1999, p. 45), or needs to estimate a smoothing curve through the highly irregular effect curve that is likely to emerge in Kalyanam and Shively's (1998, p. 24) spline regression. Hence, systematic comparisons across brands and product categories, needed for the derivation of empirical generalizations and hypothesis testing, become cumbersome to implement.

In summary, while research has validated the existence of reference-based kinked demand curves, the extant marketing literature lacks a large-scale econometric investigation of this phenomenon across product categories in retail markets, and of the moderating factors of reference-based price response at the aggregate level, where managers have to set prices and are accountable for the sales results. A systematic comparison across brands and categories is therefore needed to uncover generalizable insights, to generate concrete managerial guidelines and to identify important areas for future research. As a result, we seek to address the following research questions: (i) is there time-series evidence of non-constant and asymmetric price response across a wide variety of fast moving consumer good categories?, (ii) to what extent are such deviations from constant price response driven by historical versus competitive reference prices (HRP versus CRP), (iii) is there time-series evidence for asymmetric thresholds for gains and losses?, and (iv) do these characteristics of price response vary across brands and categories? Therefore, we extend the methodology of logistic smooth-transition autoregressive (LSTAR) models (Van Dijk, Teräsvirta and Franses 2002) to assess the impact of reference prices on short-run price elasticities.

The rest of the paper is organized as follows. In Section 2, we introduce the LSTAR methodology and specify our model. We then describe an extensive multi-category scanner database in a regional market and describe our variable operationalization (Section 3). In Section 4, we report and interpret the results of our estimation. Finally, we formulate overall conclusions and indicate limitations and areas of future research in Section 5.

2. MODELING REFERENCE-BASED PRICE ELASTICITY TRANSITIONS

In this section, we discuss the econometric representation of the model we use to examine reference-based transitions in short-run price elasticity. First, we introduce an error-correction model that allows us to consistently estimate the short-run price elasticity, even in the presence of non-stationary behavior of the respective series and/or a long-run cointegrating relationship between them. In this model, we incorporate smooth transitions of price elasticity between an 'inner' regime close to the reference point and 'outer' regimes of gains and losses. Next, we extend the smooth transition methodology to allow for (1) historical and competitive reference prices and (2) for asymmetric elasticity differences in the gains and losses regimes. Finally, we investigate whether the characteristics of non-constant price response systematically vary according to product category and brand conditions.

2.1 The Error-correction model as a generic sales-response model

We aim to correlate a brand sales variable, S_t, with various explanatory variables measuring marketing-mix efforts, like price and promotion.[1] Given our interest in the price elasticity of sales, we transform the continuously measured variables like sales and prices using the natural logarithm, obtaining the well-known power model (Hanssens, Parsons and Schultz 2001). As there can be distributed-lag and/or purchase reinforcement effects, which are most relevant for disaggregated data, and hence are likely to be found for the type of weekly scanner data we use below, it is useful to include lagged sales and prices as additional explanatory variables, resulting in the following specification:

$$\ln(S_t) = \lambda_0 + \lambda_1 \ln(P_t) + \lambda_2 \ln(S_{t-1}) + \lambda_3 \ln(P_{t-1}) + \varepsilon_t \tag{1}$$

where ε_t denotes a white-noise residual term. The model in (1) is called an autoregressive distributed lag model of order (1,1), often denoted as AD (1,1).[2] Despite its simplicity, the model has the appealing property that many often-used single-equation models, such as current-effect, partial-adjustment and serial-correlation models can be written as a special case (Hanssens et al. 2001; see also Hendry 1995, Chapters 6-7 for an elaborate discussion). Finally, the model closely resembles previous dynamic extensions of the well-known SCAN*PRO model (see e.g. Foekens et al. 1999).

Model (1) has two potential drawbacks, however. First, it may be difficult to directly interpret the parameters; for example, the total elasticity of S_t with respect to P_{t-1} is not given by λ_3. Second, when one or both variables are non-stationary (e.g. when their data-generating process has a unit root), the statistical analysis of Equation (1) is no longer straightforward, and care should be exerted to avoid the well-known spurious- regression problem documented in Granger and Newbold (1986). The latter issue is often ignored in marketing, but is quite likely to occur given Dekimpe and Hanssens' (1995) finding that 60% of the market-performance and 48% of the marketing-control variables are non-stationary.

A simple solution to the above problems is to re-write Equation (1) in error-correction form (see Hendry 1995 for details):

$$\Delta \ln(S_t) = c + \alpha_1 \Delta \ln(P_t) + \alpha_2 \left[\ln(S_{t-1}) - \alpha_3 \ln(P_{t-1})\right] + \varepsilon_t \qquad (2)$$

where Δ denotes the first differencing operator (defined *as* $\Delta X_t = X_t - X_{t-1}$), and where the parameters are linear or nonlinear functions of the parameters in (1), i.e. $[c, \alpha_0, \alpha_2, \alpha_3] = [\lambda_0, \lambda_1, \lambda_2 - 1, (\lambda_1 + \lambda_3)/(1-\lambda_2)]$. In words, model (2) says that the growth in sales[3] depends on the growth (or, rate of change) in prices and (potentially) on the deviation from an equilibrium relation between log sales and log prices.

Both abovementioned problems are addressed in this formulation. First, all parameters now have a straightforward interpretation. The α_3 parameter measures the long-run relation between log sales and log prices and can be interpreted as a long-run price elasticity (Baghestani 1991; Franses, Kloek and Lucas 1999), α_2 measures the adjustment (or, correction) towards that equilibrium in case of temporary deviations from it, while the α_0 parameter measures the short-run price elasticity. Therefore, all three parameters are expected to be negative for typical fast moving consumer goods. Second, it addresses the spurious regression problem that may emerge when regressing integrated (unit-root) series against one another by estimating α_0 (which equals λ_1 in Eq. 1) from a regression on the series' first differences, a procedure quite popular in earlier time-series applications (see e.g. Helmer and Johansson 1977). However, unlike these earlier time-series applications, our first-difference model is augmented with a lagged error-correction term. This avoids a mis-specification bias when the series are cointegrated. Indeed, in that case, relevant long-run information would erroneously be omitted from the model (Engle and Granger 1987; Franses 1998).

In this paper, we adopt Engle and Granger's (1987) two-step estimation approach. First, α_3 is estimated in an auxiliary regression from log sales on log price, this parameter is subsequently fixed in Equation (2) and the remaining parameters are estimated. This procedure leads to consistent estimates in case the variables are non-stationary, but also when they are already stationary (Franses 1998). Finally, (2) can be enlarged by including competitive prices $(P_{j,t})$ and the familiar 0/1 dummy variables for promotions such as feature and display, leading to our generic sales response model, assuming a constant price elasticity:

$$\Delta \ln(S_{i,t}) = c + \alpha_0 \Delta \ln(P_{i,t}) + \sum_{j=1}^{J-1} \phi_j \Delta \ln(P_{j,t}) + \delta_1 FEAT_{i,t} + \delta_2 DISP_{i,t} + \phi_1 \left[\ln(S_{i,t-1}) - \phi_2 \ln(P_{i,t-1}) \right] + \varepsilon_{i,t} \qquad (3)$$

In sum, Equation (3) allows to consistently estimate the short-run price elasticity parameter of interest, while accounting for potential long-run equilibrium relationships that link the series together, and controlling for other exogenous factors. While previous marketing applications focused on interpreting the long-run equilibrium relationships (Baghestani 1991; Dekimpe and Hanssens 1999; Franses et al. 1999), our prime interest is in the consistent estimation of the short-run elasticity parameter α_0.

2.2 Incorporating price-gap induced non-constant effects: smooth transition models

Model (3) still assumes a constant short-run price elasticity. We therefore introduce smooth-transition models as a flexible procedure that allows both for non-constant elasticities *and* the formal identification of the transition point and/or path between different elasticity regimes. Specifically, we propose that the price elasticity can take on different values depending on the size of the gap *(GAP_t)* between the focal brand's current price and a reference price (defined below). To that extent, we can write model (3) as:

$$\Delta \ln(S_{i,t}) = c + [\alpha_0 + F(GAP_t)\alpha'_0] \Delta \ln(P_{i,t}) + \sum_{j=1}^{J-1} \phi_j \Delta \ln(P_{j,t}) + \delta_1 FEAT_{i,t} + \delta_2 DISP_{i,t} + \phi_1 \left[\ln(S_{i,t-1}) - \phi_2 \ln(P_{i,t-1}) \right] + \varepsilon_{i,t} \qquad (4)$$

where $F(GAP_t)$ is a continuous transition function bounded between 0 and 1.

Model (4) can be interpreted in two ways (Van Dijk, Teräsvirta and Franses 2002). On the one hand, it can be thought of as a regime-switching model that allows for two possible regimes, a short-run price elasticity of α_0 versus $\alpha_0 + \alpha'_0$, associated with the respective extreme values of the transition function, $F(GAP_t)$=0 and $F(GAP_t)$=1, and where the transition of one regime to another can be smooth. On the other hand, one could also look at Model (4) as allowing for a continuum of elasticity values, each associated with a different value of $F(GAP_t)$ between 0 and 1. In this paper, the regime interpretation is adopted (i.e. price is either inside or outside the inner regime around a reference price, as operationalized below), with a smooth transition between both regimes. Often, the number of observations in the transition phase is not large, and hence, it seems most useful to focus on the price elasticity in the two regimes before and after the transition rather than on the price elasticity in the transition phase itself. The functional form of $F(GAP_t)$ can be logistic, implying a single transition between two regimes, or quadratic logistic, implying two transition points. We develop the exact specification for $F(GAP_t)$ based on the extensive marketing literature on the nature of the reference price (historical versus competitive) and asymmetric price response and threshold sizes for gains and losses.

First, the conceptualisation, and therefore the modelling, of price gaps has two distinct traditions in marketing (Klein and Oglethrope 1987). The first approach considers an historical, or memory-based reference price and thus compares the focal brand's current price with past prices (Lattin and Bucklin 1989; Kalyanaram and Little 1994). The second approach considers a competitive or stimulus-based reference price and thus compares the focal brand's current price with the current prices of competitors (e.g. Hardie et al. 1993; Rajendran and Tellis 1994). Recently, both experimental (e.g. Bolton et al. 2003) and quantitative evidence (e.g. Briesch et al. 1997) suggest that both types of reference prices are important, so we want to allow for both.

Second, reference-based price response could be asymmetric to gains (price decreases) versus losses (price increases) (Kalyanaram and Little 1994). For one, the threshold size could differ, as Han et al. (2001) find larger thresholds for gains versus losses in the coffee category. Moreover, the elasticity difference could differ for gains versus losses, as consumers react more to perceived price losses than to price gains (Kalyanaram and Winer 1995) or vice versa (Greenleaf 1995; Krishnamurthi et al. 1992). This phenomenon implies we should model $F(GAP_t)$ using a three-regime logistic function, as it enables threshold asymmetry with a lower threshold β_1 with elasticity change for gains α_1, and an upper threshold β_2, with elasticity change for losses α_2. Therefore, we substitute α_0 in equation (4) with the following expression:

$$\alpha_0 + \alpha_{1,HRP}\left(1+\exp\left[-\gamma\left(\log P_t - \log P_{t-1} - \beta_{1,HRP}\right)\right]\right)^{-1} + \alpha_{2,HRP}\left(1+\exp\left[-\gamma\left(\log P_t - \log P_{t-1} - \beta_{2,HRP}\right)\right]\right)^{-1}$$
$$+\alpha_{1,CRP}\left(1+\exp\left[-\gamma\left(\frac{P_t - \frac{1}{J-1}\sum_1^{J-1} P_t}{\frac{1}{J-1}\sum_1^{J-1} P_t} - \beta_{1,CRP}\right)\right]\right)^{-1} + \alpha_{2,CRP}\left(1+\exp\left[-\gamma\left(\frac{P_t - \frac{1}{J-1}\sum_1^{J-1} P_t}{\frac{1}{J-1}\sum_1^{J-1} P_t} - \beta_{2,CRP}\right)\right]\right)^{-1} \tag{5}$$

with α_0 the constant price elasticity in the 'inner regime'[β_1 , β_2] around the reference price, α_{HRP} and α_{CRP} the additional price elasticity outside this regime for respectively the historical and the competitive reference price definition, $\beta_{1,HRP}$, $\beta_{1,CRP} < 0$ and $\beta_{2,HRP}$, $\beta_{2,CRP} > 0$ the price thresholds for respectively gains and losses, and parameter γ the smoothness of the transition curve, all of which are estimated in our application. Our model detects that the price difference exceeds the historical price threshold as follows (a similar rationale applies for competitive reference price). The exponential function equals zero when the price difference equals the price threshold. In contrast, when $logP_t$ - $logP_{t-1} < \beta_{1,HRP}$, i.e. the current price represents a clear gain over the previous price, and the price elasticity smoothly transitions into α_0 + $\alpha_{1,HRP}$. Likewise, when $logP_t$ - $logP_{t-1} > \beta_{2,HRP}$, i.e. the current price represents a clear loss over the past price, the exponential function equals 1 and the price elasticity becomes α_0 + $\alpha_{2,HRP}$. Figures 1 and 2 visualize a three-regime logistic STAR-model with $\alpha_{1,HRP} < 0$; $\alpha_{2,HRP} > 0$; $\beta_{1,HRP} = -0.2$; $\beta_{2,HRP} = 0.1$ and $\gamma = 50$.[4]

-- Insert Figures 1 and 2 around here --

In this example, assimilation/contrast effects are observed around the lower threshold; a negative value of $\alpha_{1,HRP}$ implies a higher price sensitivity below this threshold. Such thresholds arise when consumers do not change their buying intentions unless the price change exceeds the threshold level (Kalyanaram and Little 1994). In contrast, a positive value of $\alpha_{2,HRP}$ implies saturation effects; i.e. a lower price sensitivity beyond the upper threshold. Such phenomenon may be caused by consumers perceiving price changes as less than they actually are (Gupta and Cooper 1992) or by limitations to consumer price reaction, such as upper sales limits to stockpiling ability (Battberg et al. 1995) and lower sales limits because of strong customer needs and loyalty (van Heerde 1999).

2.3 Model comparison tests for reference price type and asymmetry

There are several options to examine whether models with one or more transition functions are a useful way to fit the data. For one, we can follow the test strategies in Van Dijk, Terasvirta and Franses (2002). Unfortunately, while these test statistics are very powerful in indicating the presence of non-constant effects, they are not so powerful in distinguishing which specific functional form or transition variable is most relevant (ibid). Therefore, we instead estimate and compare 4 different models and select the best model based on the Akaike Information Criterion (AIC), which balances model fit with model complexity (McQuarrie and Tsai 1998). In this way, we compare the full model to a model with only historical reference-based price response ($\alpha_{1,CRP} = \alpha_{2,CRP} = 0$), only competitive reference-based price response ($\alpha_{1,HRP} = \alpha_{2,HRP} = 0$), and the constant-elasticity model in equation (4). AIC-based model selection reveals for each brand whether historical reference prices, competitive reference prices, or both affect the short-run price elasticity.

Within the selected model for each brand, we next test for asymmetry in threshold size and elasticity difference for gains and losses. We assess this asymmetry with a binomial test for the estimated parameters $|\beta_1|$ versus $|\beta_2|$ and α_1 versus α_2. Note too that when the thresholds $|\beta_1|$ and $|\beta_2|$ are equal, our model collapses to a symmetric three-regime logistic model with a single threshold. Detailed estimation results, available upon request, indicate that this model is consistently rejected by the data.

3. DATA DESCRIPTION AND OPERATIONALIZATION

3.1. Data description

The database consists of scanner records for 25 product categories from a large mid-western supermarket chain, Dominick's Finer Foods. With 96 stores in and around Chicago, this chain is one of the two largest in the area. Relevant variables include unit sales at the UPC level, retail and wholesale price (appropriately deflated using the Consumer Price Index for the area), price specials, promotions and new-product introductions[5]. A maximum of 399 weeks are available for each category, from September 1989 to May 1997.[6] Sales are aggregated from SKU to the brand level, and we follow Pauwels et al. (2002) in adopting static weights (i.e. average share across the sample) to compute the weighted price, rather than the dynamic (current-period) weights. All data are given at the weekly level. Summary information on the data set is provided in Table 1. Focusing on the top-four brands, we analyze a total of 100 brands.

---Insert Table 1 about here---

3.2 Impact of brand and category characteristics on price elasticity transitions

The second-stage of our research explores the circumstances under which (1) historical and competitive reference prices contribute to non-constant price elasticity, (2) the price elasticity difference (outside versus inside the price gap) is higher versus lower, and (3) the threshold size is larger for gains versus losses. Based on previous literature, we consider both factors that may affect price elasticity (Narasimhan et al. 1996), and factors that may affect reference price accessibility, i.e. the ease with which reference prices are accessed from memory, and diagnosticity , i.e. the extent to which such information is relevant (Lynch et al. 1988, Mazumdar and Papatla 2000). Such factors include the brand characteristics (1) expensiveness of the brand relative to the other brands in the category, (2) brand price volatility, (3) brand market-share, and (4) national brand versus private label, and the category characteristics (5) category expensiveness (6) category price volatility, (7) category price spread, (8) category concentration, (9) SKU proliferation, (10) product storability, (11) impulse (versus planned) purchase, and (12) category purchase frequency. Methodologically, the second stage analysis uses weighted-least squares regression, using as weights the inverse of the standard errors of the first-stage estimates.

3.3 Variable operationalization

Historical Reference Price (HRP). The historical reference price is the price that the consumer expects to encounter for a brand (Mayhew and Winer 1992). Following previous research on aggregate-level data (Raman and Bass 2002; Putler 1992), we model the historical reference price (HRP) of period *t* as the brand-specific price in the period *t-1*.[7]

Competitive Reference Price (CRP). We operationalize competitive reference price (CRP) as the mean of the prices of all the other brands (other than the focal brand) in the category. The advantage of this measure is that it captures the effect of all the other brands (Kumar, Karande and Reinartz 1998; Rajendran and Tellis 1994).

Brand expensiveness. Following Raju (1992), we first computed the regular price (highest price over the data period) of each brand. A brand's expensiveness relative to other brands is calculated by dividing the brand's regular price by the market share weighted average of the regular prices of all the brands in the category.[8]

Brand price volatility. We first computed regular price as defined above. Next, for every week, we computed the difference between the price in that week (P_t) and the regular price as a fraction of the regular price. The volatility in price is set equal to the average of the deviation from the regular price over the data period. This metric is thus operationalized in a manner similar to the 'variability in category sales' measure in Raju (1992).[9]

Brand ownership. We use a dummy variable to capture the distinction between private labels and national brands. This variable takes on a value of 1 if the brand is a private label, and 0 if it is a national brand.

Brand market share. The brand's market share is operationalized as the average volume-based share of the brand as in Srinivasan, Pauwels, Hanssens and Dekimpe (2003).

Category expensiveness. As with brand expensiveness, we first computed the regular price (highest price over the data period) of each brand. The category level measure is calculated by the market share weighted average of the regular prices of the brands in the category (see, for example, Raju 1992).

Category price volatility. The category level measure is operationalized similar to the brand price volatility with the exception that the price at the category level is the market share weighted average of the regular prices of the brands in the category.

Category price spread. This variable is operationalized as the ratio of the difference between the maximum price and the minimum price of all brands to the minimum price in a given week in the category (Briesch et al. 1997).

Category concentration. We measure the category's competitive structure by market concentration, following previous work in industrial organization and marketing (Bowman and Gatignon 1995; Caves 1998), as the sum of the shares of the top-three brands in the category.

SKU proliferation. The number of SKUs in the category (Narasimhan et al. 1996; Srinivasan, Pauwels and Nijs 2003) is included to capture the extent of brand proliferation.

Impulse Buying and Ability to Stockpile. We use the Narasimhan et al. (1996) storability and impulse-buy scales to construct dummy variables indicating whether the product is considered perishable or storable (=1), and whether or not it is typically associated with an impulse versus a planned purchase (=1).[10]

Category purchase frequency (Interpurchase time). We used the purchase cycle time measures reported by the IRI Marketing Factbook, taking the average time reported for each category over the relevant data period.

4. EMPIRICAL RESULTS

4.1 Empirical generalizations on non-constant price elasticity

Based on the AIC, the constant elasticity model is selected for 23% of all brands, while 28% demonstrate historical reference prices, 24% competitive reference prices and 25% both (full model). Interestingly, these results partly confirm and partly extend previous research. First, we do indeed find evidence for both historical and competitive reference price response, in line with Kumar, Karande and Reinartz (1998), Mayhew and Winer (1992), Rajendran and Tellis (1994), and Mazumdar and Papatla (2000). In contrast, we find that the full model is preferred for one out of four brands whereas these authors reported it fits best in all studied situations. Moreover, competitive reference price is not more often (Hardie, Johnson and Fader 1993; Kumar et al.1998) but less often (Briesch et al. 1997) the main contributor to non-constant price response.

Table 2 presents the summary statistics of the parameter estimates.

--- Insert Table 2 about here ---

Across all brands, we find that the base elasticity α_0 = –2.29 (standard deviation =0.20), consistent with empirical generalizations from meta-analysis (Tellis 1988; Bijmolt, van Heerde and Pieters 2003). For historical reference prices, the threshold size is larger for gains (20%) than for losses (12%), as reported by Han et al. (2001). Interestingly, we find increased price sensitivity for gains (-0.41), but decreased price sensitivity for losses (0.81). The former is consistent with assimilation/contrast effects (latitude of acceptance) for price reductions (e.g. Kalyanaram and Winer 1994). The latter represents saturation effects for large price increases, which mirrors the saturation effects for price discounts reported by van Heerde (1999). This phenomenon may be due to hardcore brand loyalty or to consumers not fully encoding the full size of the price increase vis-à-vis the last purchase occasion (Alba et al. 1991; Gupta and Cooper 1992). For competitive reference prices, the threshold size is smaller for gains (3%) than for losses (16%), and saturation effects emerge both for gains (0.33) and for losses (0.15). This finding implies that even small deviations from competitive reference prices affect brand sales, while the price elasticity decreases for large deviations. Such market-level results are consistent with price recall studies in which consumers could easily price rank competitors even if they did not encode exact prices (Dickson and Sawyer 1990). Binomial tests conclude that the price elasticity significantly differs for the inner versus outer regimes and that threshold sizes for gains and losses significantly differ for both HRP and CRP. Moreover, the elasticity change for gains versus losses significantly differs for HRP, but not for CRP.

4.2 Moderating factors of price elasticity transitions

Tables 3 and 4 show the results for the exploratory second-stage analysis, which relates type of reference price, elasticity difference and size of price threshold for gains and losses to brand and category characteristics. We only display results for those variables that are significantly explained by these moderating factors (as measured by the F-statistic significant at the 5% level)

--- Insert Tables 3 and 4 about here ---

4.2.1 Moderating factors of model selection, base price elasticity and elasticity change

Table 3 reports the moderator results for the selection of the constant-elasticity model and for the model with historical reference prices, and for the base elasticity α_0 and the elasticity difference for gains based on the historical price reference $\alpha_{1,HRP}$ (competitive reference price model selection and the other elasticity differences do not vary systematically according to our moderating variables).

Columns 2-3 show that, while constant elasticity models dominate for store brands, for expensive categories and impulse-buy products, historical reference prices more often play a role for national brands, inexpensive categories and planned purchase products. In all three cases, historical reference prices are more accessible to consumers. First, national brands are more visible to consumers as they often spend much effort in brand building and promoting activities, which help consumers to create and maintain strong positive memory associations, strong brand preference and a well-developed cognitive structure (Johnson and Russo 1978; Keller 1998). As a result, consumers are likely to have better assimilation and recall of the prices of national brands and thus use historical reference prices in their price assessment (Rajendran and Tellis 1994; Biehal and Chakravarti 1982). Second, reference-based ‘transaction utility’ (Thaler 1985) is likely to be more important for inexpensive categories, while consumers are more occupied with the price itself for big ticket items and therefore show a more constant elasticity for such products. Finally, planned purchases engage more “intentional learning”, including active search and memorization of exact prices (Mazumdar and Monroe 1990). Therefore, prices for planned purchase products are easier to recall from memory, and historical reference prices dominate (Mazumdar and Papatla 2000).

Additionally, historical reference price models are more frequent for categories with low price volatility and high purchase frequency. In both situations, memory-based reference prices are more accessible (Moon and Russell 2002), and more diagnostic (Briesch et al. 1997).

Column 4 in table 3 shows that the base price sensitivity is higher for brands with high price volatility and for storable products. The former result strengthens the empirical generalization that promotional intensity increases price sensitivity (Mela et al. 1998, Nijs et al. 2001). The latter result follows from consumer ability to stockpile large quantities of the storable product at low prices, and thus to reduce purchases at high prices (Bell et al. 1999). In contrast, the base price sensitivity is lower for high-share brands in categories with high SKU-proliferation. First, high-share brands are likely to operate on the flat portion of their sales response functions (Blattberg et al. 1995; Bell et al. 1999). These brands therefore experience 'excess' loyalty and lower selective demand effects (Fader and Schmittlein 1993). Likewise, consumer loyalty is more prominent in concentrated categories. Third, categories with many SKUs demonstrate lower price sensitivity, consistent with the higher product differentiation (Narasimhan et al. 1996) and the dilution of price attention in such crowded categories (Srinivasan et al. 2003).

As the current price represents a gain over the historical reference price, the price elasticity increases more for categories with high price volatility and SKU-profileration (column 5 in table 3). In contrast, it increases less for storable and impulse-buy products with a long purchase cycle. The first result indicates that price volatility increases the salience and thus accessibility of this marketing instrument to consumers, which strengthens their response to price promotions (Mela et al. 1997). The effects of SKU proliferation attenuate its impact on the base price elasticity: once the price promotions reaches the gains threshold, the promotion stands out enough to lift the (lower) base price elasticity. The mirror argument applies for storability. Finally, impulse-buy products and products with a long purchase cycle face a more constant price promotional elasticity (Narasimhan et al. 1996).

4.2.2 Moderating factors relating to threshold size

Table 4 presents the moderator results for threshold size. Based on the historical reference price (columns 2-3), high-share brands have a larger threshold for gains and for losses. This finding logically follows from the definition of price elasticity, as high-share brands need stronger price changes to affect their base price elasticity (van Heerde et al. 2003). Second, the losses threshold is higher for brands with high price volatility. In other words, saturation effects set in later for brands that teach consumers to buy on deal (Mela et al. 1997). Third, saturation effects set in later in categories with a high price spread and for planned purchases. Both situations enable competitive price comparison (Briesch et al. 1997).

For competitive reference prices (columns 4-5 in table 4), expensive brands with high price volatility have higher thresholds for gains and losses. Again, price is more salient for these brands, so that saturation effects set in later. Moreover, the losses threshold is higher in categories with lower price volatility, higher price spread and higher concentration. First, consumers face fewer price changes in such categories, so that price increases are more salient and saturation effects set in later. Likewise, the presence of a few major brands with a high price spread enables consumer price comparison among brands (Narasimhan et al. 1996; Briesch et al. 1997).

4.3 Managerial relevance of non-constant price elasticity

In order to illustrate the managerial relevance of price elasticity transitions, we report and contrast the price impact on performance under constant-elasticity versus under reference-based price response. First, we display the price elasticity of sales in Figure 3. Next, we report the implications of three levels of price changes, based on the estimated thresholds and the pricing history of the brands, on (a) unit sales, (b) revenues (sales * retail price), and (c) retailer gross margin (sales * unit margin). For this illustrative purpose, we select a brand in the refrigerated juice category, with a typical base price elasticity of -2.26 and for which both historical and competitive reference prices matter. Figures 3 and 4 display the predicted sales change by widening the price gap with respectively the historical and the competitive reference price.

--- Insert Figures 3 and 4 around here ---

Figure 3 illustrates that the price sensitivity increases once the historical reference price gain threshold is crossed. In contrast, the price sensitivity decreases once the threshold for losses is crossed. Moreover, note the asymmetry in threshold sizes, with the gain threshold at 23% discount versus the losses threshold at 12% increase over the reference price. In managerial terms, the brand obtains more bang-for-the-buck with e.g. a 30% promotion than with a 10%

promotion. However, managers should beware that such discounts lower the reference price and thus the effectiveness of future price promotions (Kopalle et al. 1996). The opposite implication applies for price increases: one 20% price increase yields less % sales loss than two price increases of 10%. In contrast, Figure 4 shows saturation effects for both gains and losses over the competitive reference price: the price sensitivity decreases once the thresholds of around 30% are crossed. Tables 5 and 6 further explore the performance implications of typical price changes

--- Insert Tables 5 and 6 around here ---

Table 5 shows that a 10% price change leads to identical sales, retailer revenue and retailer margin response for both the historical reference price model and the constant elasticity model. Indeed, this price change is below the threshold for both gains and losses. At the 25% price change level, the constant elasticity model still yields similar effect estimates for price decreases (within 2% of the HRP estimates), but not for price increases (2.21 times higher than those for the HRP estimates). This difference illustrates threshold asymmetry and the ability of the smooth transition model to capture both subtle and strong deviations from the constant elasticity model. Finally, a 30% price change clearly crosses the threshold for both gains and losses and thus yields substantial model estimate differences in both cases. For instance, the estimated sales response to 30% price discounts is 12% higher when the historical reference price effect is considered. Knowledge of such reference-based price thresholds is thus important to brand manufacturers, which have considerable control over their brand pricing policies given the high retailer pass-trough rates (Besanko et al. 2003, Pauwels 2003). Interestingly, the impact of reference prices on retailer revenue and gross margin effect estimates are even stronger. Most notably, a 20% price hike decreases performance four times more under constant elasticity versus the HRP model.

For the competitive reference price definition, Table 6 shows that a 10% price change yields identical performance response for both the constant elasticity and the competitive reference price model. In other words, brand managers should beware that even small differences with competitive prices engage consumer response. Given the high thresholds, even a 25% price change has similar effects for both models (within 3% difference). In contrast, price changes of 30% result in considerably lower sales response due to CRP-based saturation effects. The over-estimation of sales effects by the constant elasticity model is 13% for gains and 25% for losses. Note that, though the threshold sizes are similar, the saturation effects are about double as high for losses versus gains. Again, retailer revenue and gross margin implications are similar than sales implications, but of a higher magnitude. In particular, note that the constant elasticity and the CRP-model select a different price discount to optimize (short-run) retailer gross margin benefits, respectively 30% and 25%. This observation is particularly relevant as retailers set prices for all competing brands and thus may influence competitive reference price directly by choosing either negative or positive cross-brand pass-through (Besanko et al. 2003). When the retailer acts to maximize brand profits, as observed by Hall et al. (2002) and Pauwels (2003), our analysis supports a retail policy of increasing competitive prices to make the brand's promotion stand out, but only up to the point when saturation effects set in. Evidently, when the retailer acts to maximize category profits (Zenor 1994), further analysis is needed to determine the desirability of such policy.

In summary, the constant elasticity model substantially under-estimates the performance impact of large discounts over historical reference prices, and substantially over-estimates the performance impact of large increases over historical reference prices and of price changes vis-à-vis competitive reference prices. Therefore, once the threshold is crossed, it is financially important for managers to account for assimilation/contrast effects and saturation effects.

5. CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS

This study introduced the methodology of smooth transition models to investigate the evidence for non-constant price response across a wide range of fast moving consumer good categories. Based on our analysis of 100 brands, we find that 28% demonstrate historical reference prices, 24% competitive reference prices and 25% both. For historical reference prices, the threshold size is larger for gains (20%) than for losses (12%) and the assimilation/contrast effects for gains (-0.41) are smaller than the saturation effects for losses (0.81). For competitive reference prices, the threshold size is smaller for gains (3%) than for losses (16%), and saturation effects emerge both for gains (0.33). Finally, the second-stage analysis reveals the moderating role of both brand and category characteristics that affect reference-price accessibility and diagnosticity. Historical reference prices more often play a role for national brands, for planned purchase and in inexpensive categories with low price volatility and high purchase frequency. When price discounting, high-share brands face a larger latitude of acceptance. When raising prices, saturation effects set in later for brands with high price volatility and for categories with high price spread and for planned purchases. As for competitive reference prices, saturation effects set in later for expensive brands with high price volatility and in categories with lower price volatility, higher price spread and higher concentration.

The managerial relevance of our findings is illustrated for a representative brand in the refrigerated juice category. Price changes of 10% yield similar performance effects for the constant elasticity and the reference price models, as all threshold sizes exceed 10%. Once we increase the price change to cross the respective (asymmetric) thresholds, the constant elasticity model estimates start to differ substantially from those of our selected models. In particular, the constant elasticity model substantially under-estimates the performance impact of large discounts over historical reference prices, and substantially over-estimates the performance impact in all other cases. In other words, the smooth transition model captures both strong and subtle non-constant performance response near the asymmetric threshold for gains and losses.

Finally, this study has several limitations, which provide promising areas for future research. First, we did not model consumer heterogeneity as we aimed to generate market-level guidelines for fast moving consumer good retailers, who have limited ability to price discriminate. Second, we did not model the role of feature and display on reference price response. Likewise, richer datasets would allow us to account for non-constant response to changes in other marketing-mix variables, such as advertising. Third, our framework could be expanded by allowing for more than 3 regimes of non-constant elasticity. Fourth, future research could allow for non-constant relations between the price elasticities and the price thresholds and the second-stage characteristics as well as the potential endogeneity of these characteristics. Finally, our findings are based on data from well-established, mature product categories. More research is needed on whether these findings can be generalized to new product categories.

Fine-tuning prices requires deeper knowledge of non-constant price response, and academic research has only started to address this pressing managerial issue (Bucklin and Gupta 1999). To this end, the current paper provides market-level evidence on historical and competitive reference prices and of asymmetry for gains versus losses on three levels: the threshold size, the sign and the magnitude of the elasticity difference. Moreover, the specifics of non-constant price response differ systematically across brands and categories. Especially retailers may benefit from these specific results, as they set all competitive prices in a category. Therefore, they are able to adapt the competitive reference price in order to either reduce the sales impact of price increases or to enhance brand sales response to price discounts. Together with research on dynamic pricing effects, such knowledge enables the move towards an optimization model for retail price fine-tuning across brands and categories.

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Table 1: Data description

Category	*Starting date*	*Ending Date*	*Weeks*
Bottled juice	09/14/1989	05/01/1997	399
Cereals	09/14/1989	02/09/1995	283
Cheese	09/14/1989	05/01/1997	399
Cookies	09/14/1989	10/06/1994	265
Crackers	09/14/1989	09/08/1994	261
Canned soup	09/14/1989	04/17/1997	397
Dish detergent	09/14/1989	05/01/1997	399
Front-end candies	09/14/1989	05/01/1997	399
Frozen dinners	05/28/1992	05/01/1997	258
Frozen juice	09/14/1989	05/01/1997	399
Fabric softener	09/14/1989	05/01/1997	399
Laundry detergents	09/14/1989	05/01/1997	399
Oatmeal	06/06/1991	05/01/1997	309
Paper towels	09/14/1989	05/01/1997	399
Refrigerated juice	09/14/1989	05/01/1997	399
Soft drinks	09/14/1989	07/14/1995	253
Shampoos	02/20/1992	02/09/1995	156
Snack crackers	09/14/1989	10/06/1994	265
Toothbrushes	09/14/1989	05/01/997	399
Canned tuna	09/14/1989	01/11/1996	331
Toothpaste	09/14/1989	05/01/1997	399
Bathroom tissue	09/14/1989	05/01/1997	399

Table 2: Summary of key results across categories (mean and standard errors)

	Elasticity difference Gains α_1	***Elasticity difference Losses α_2***	***Threshold Gains β_1***	***Threshold Losses β_2***
Historical Reference Price	-0.41 (0.14)	0.81 (0.25)	-0.20 (0.02)	0.12 (0.02)
Competitive Reference Price	0.33 (0.11)	0.15 (0.06)	-0.03 (0.002)	0.16 (0.01)

Table 3: Brand and category moderators model selection and price elasticity *

Variable	*Constant Elasticity model*	*Historical RP Model*	*Base elasticity*	*Elasticity difference HRP Gain*
Brand Price Volatility	0.017	-0.005	**-0.051**	0.122
	(.15)	(.74)	**(.05)**	(.11)
National Brand	**-0.218**	**0.252**	0.185	-0.393
	(.08)	**(.08)**	(.40)	(.45)
Brand Market Share	-0.285	0.341	**1.100**	-0.451
	(.19)	(.18)	**(.01)**	(.53)
Category Expensiveness	**0.031**	**-0.049**	0.039	0.134
	(.00)	**(.00)**	(.20)	(.19)
Category Price Volatility	0.009	**-0.022**	0.024	**-0.149**
	(.41)	**(.08)**	(.33)	**(.04)**
Category Concentration	-0.180	0.157	**1.383**	-0.233
	(.43)	(.55)	**(.00)**	(.80)
Cat. SKU- proliferation	0.000	0.000	**0.001**	**-0.0004**
	(.63)	(.70)	**(.00)**	**(.09)**
Product Storability	0.039	-0.038	**-0.501**	**0.773**
	(.70)	(.75)	**(.00)**	**(.06)**
Product Impulse Buy	**0.401**	**-0.297**	-0.154	**1.274**
	(.04)	**(.05)**	(.45)	**(.06)**
Product Purchase Cycle	-0.002	**0.005**	-0.006	**0.030**
	(.42)	**(.07)**	(.33)	**(.00)**

* standardized coefficients with p-values in parentheses; estimates significant at the 10% level in bold. For exposition ease, we only show the moderating variables that obtained 10% significance for any explained parameter.

Table 4: Moderating role of brand and category characteristics on price thresholds*

Variable	*HRP Gain Threshold*	*HRP Loss Threshold*	*CRP Gain Threshold*	*CRP Loss Threshold*
Brand Relative Price	0.093	-0.021	**0.775**	**1.114**
	(.51)	(.86)	**(.00)**	**(.00)**
Brand Price Volatility	0.021	**-0.023**	**0.030**	**0.054**
	(.15)	**(.04)**	**(.00)**	**(.00)**
Brand Market Share	**-0.292**	**0.289**	-0.094	0.070
	(.03)	**(.05)**	(.65)	(.82)
Category Price Volatility	0.006	0.000	-0.017	**-0.028**
	(.61)	(.96)	(.28)	**(.01)**
Category Price Spread	0.034	**0.170**	-0.140	**0.390**
	(.79)	**(.10)**	(.32)	**(.02)**
Category Concentration	-0.167	-0.086	0.072	**0.898**
	(.24)	(.59)	(.71)	**(.01)**
Product Impulse Buy	0.086	**-0.218**	-0.027	-0.150
	(.45)	**(.08)**	(.88)	(.60)

*standardized coefficients with p-values in parentheses; estimates significant at the 10% level in bold. For exposition ease, we only show the moderating variables that obtained 10% significance for any explained parameter.

Table 5: Performance response based on HRP for the second refrigerated juice brand

	Smooth transition model	*Constant elasticity model*	*Smooth transition model*	*Constant elasticity model*
	Price decrease		*Price increase*	
Sales response (in 1000)				
10% price change	105	105	-105	-105
25% price change	273	267	-117	-259
30% price change	353	312	-172	-309
Retailer Revenue response (in $K)				
10% price change	17	17	-17	-17
25% price change	34	30	-16	-64
30% price change	39	32	-30	-80
Retailer Gross Margin response (in $K)				
10% price change	4.2	4.2	-4.2	-4.2
25% price change	8.45	7.45	-4.05	-16.05
30% price change	9.7	7.95	-7.55	-20.05

Table 6: Performance response based on CRP for the second refrigerated juice brand

	Smooth transition model	***Constant elasticity model***	***Smooth transition model***	***Constant elasticity model***
	Price decrease		***Price increase***	
Sales response (in 1000)				
10% price change	105	105	105	-105
25% price change	260	267	-218	-229
30% price change	275	312	-220	-276
Retailer Revenue response (in $K)				
10% price change	17	17	-17	-17
25% price change	29	30	-50	-54
30% price change	25	32	-46	-74
Retailer Gross Margin response (in $K)				
10% price change	4.2	4.2	-4.2	-4.2
25% price change	**7.2**	7.45	-12.05	-14.05
30% price change	6.2	**7.95**	-11.95	-17.95

Figure 1: Transition function for the Three-Regime Logistic STAR-model

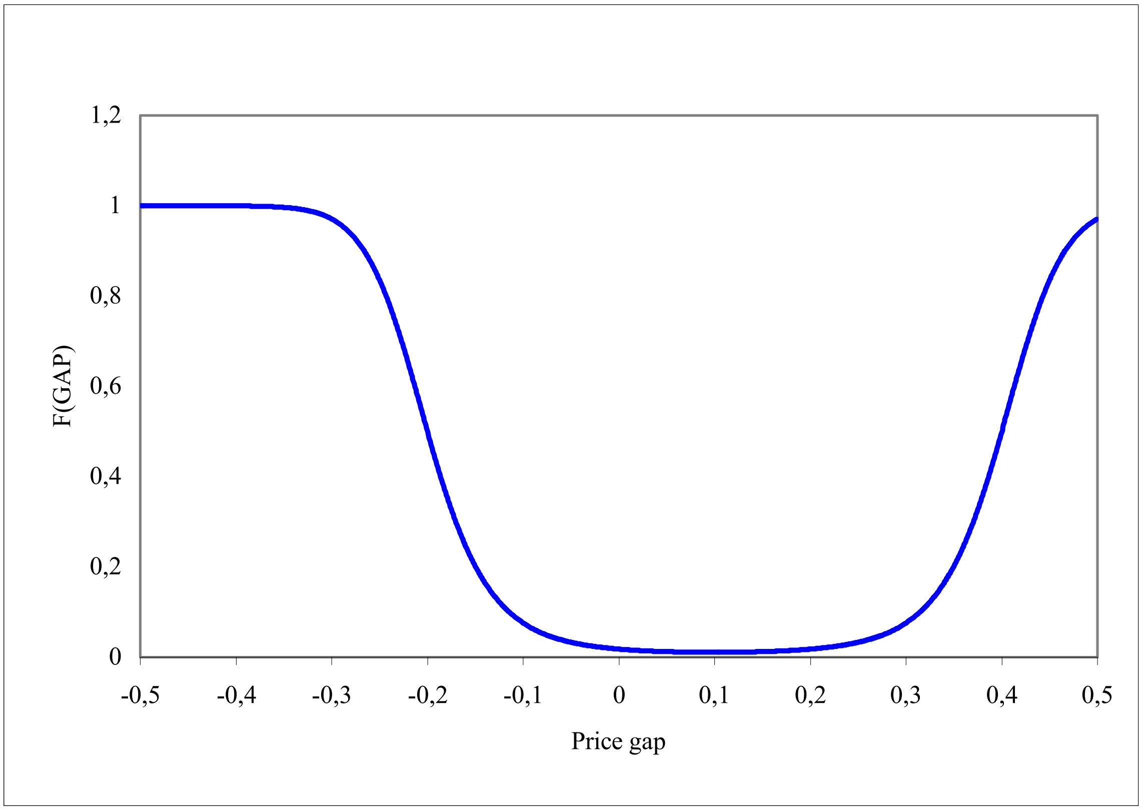


Figure 2: Sales response to price changes in the Three-Regime Logistic STAR-model

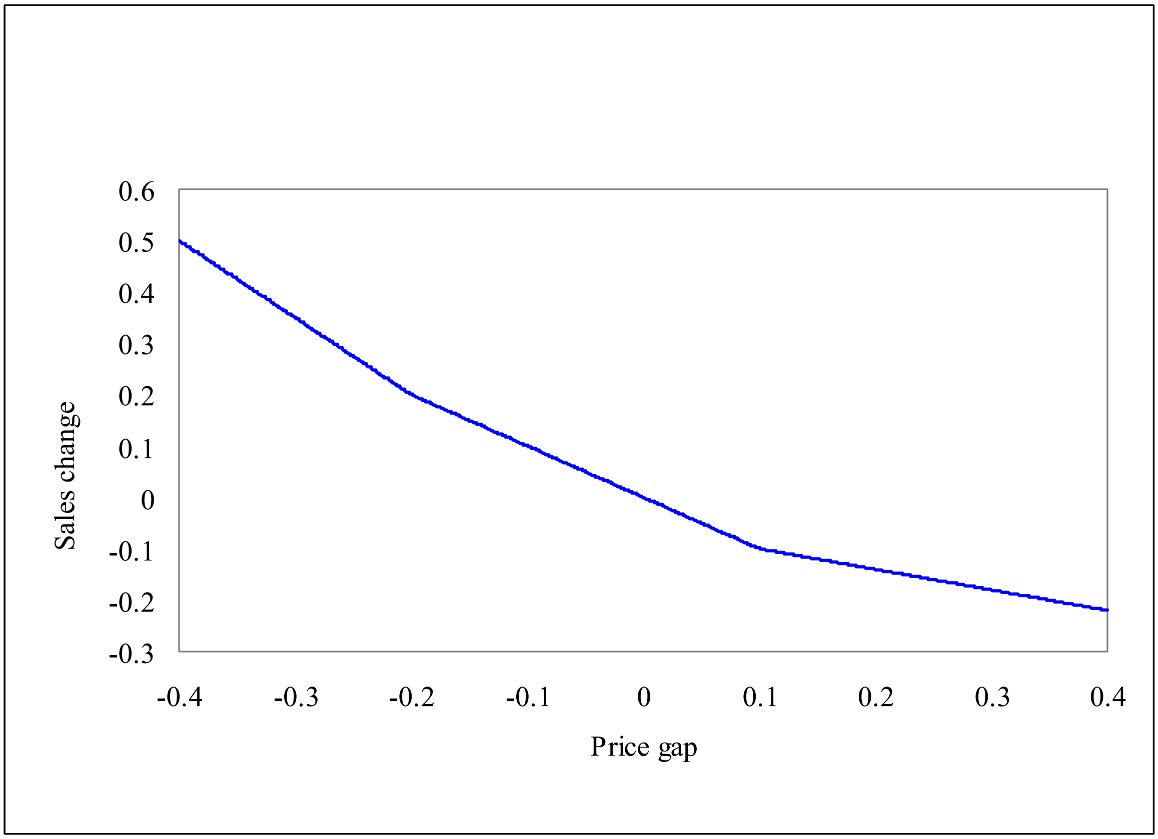


Figure 3: Change in sales as a function of the gap with Historical Reference Price

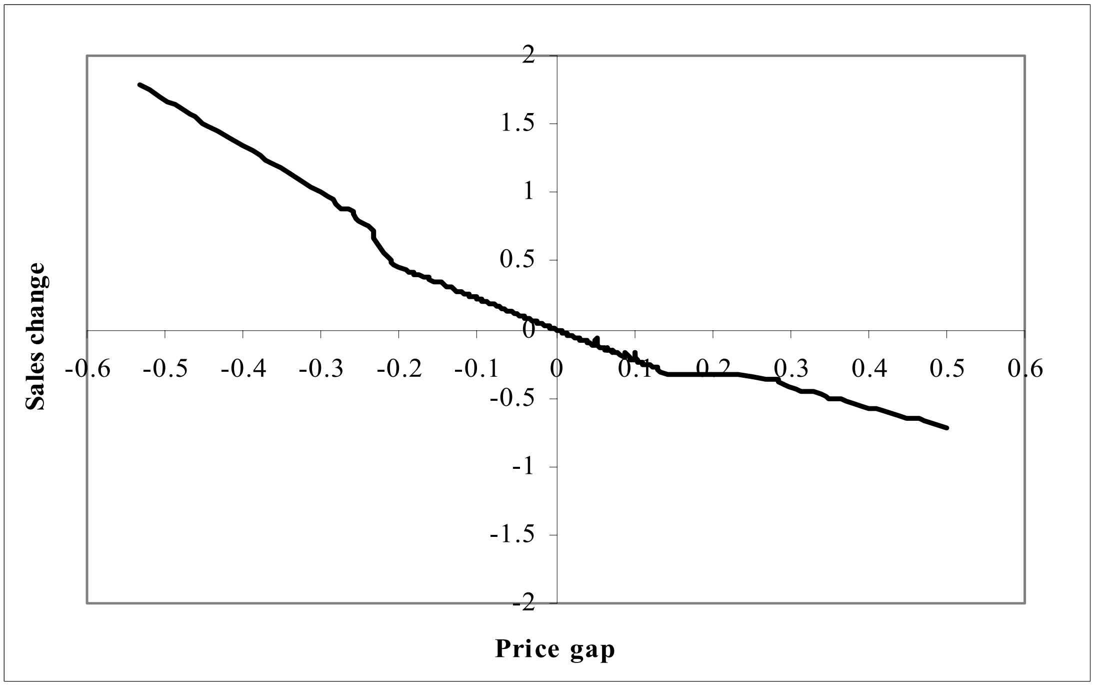
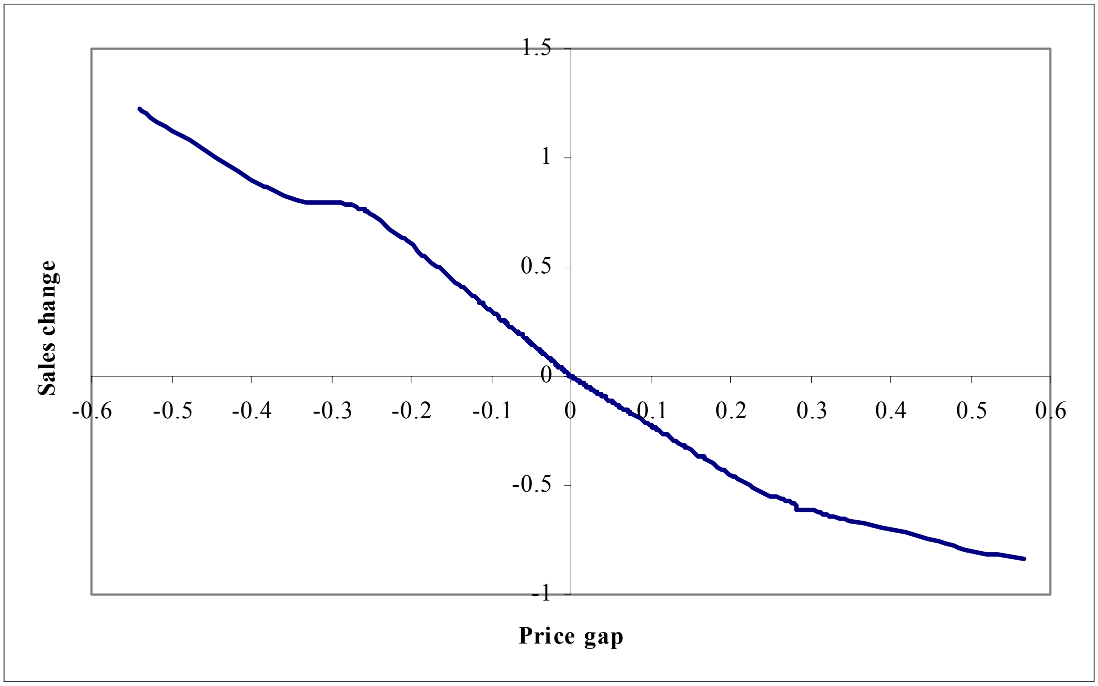


Figure 4: Change in sales as a function of the gap with Competitive Reference Price



Endnotes

1 Our dataset lacks information on distribution and advertising, which is common for scanner-data in marketing.

2 Higher-order lags could easily be included, but the AD (1,1) model was found to be an adequate parameterization for almost all brands considered in our data set. Furthermore, in recent VAR-based studies, the typical number of lags for models estimated in frequently purchased consumer goods was one (Srinivasan et al. 2003; Nijs et al. 2001)

3 This is because the first differences of logged variables are approximately growth rates.

4 These illustrative values were chosen based on our empirical estimation.

5 We control for major product introductions by dummy variables in our regression.

6 Some categories have fewer than 399 weeks of data due to missing observations.

7 Although the marketing literature has seen several competing HRP operationalizations, Kalwani et al. (1990) find little difference in fit across these alternatives. Indeed, we verified that our results are robust to using exponentially lagged past prices instead of past price (Briesch et al. 1997).

8 We assessed the robustness of our findings to the alternative measures of price volatility; our results remain robust to this issue.

9 Additionally, an alternate operationalization for the brand's price volatility is the coefficient of variation (the ratio of the standard deviation to the mean) in the brand's price; however, we obtained similar results with this alternative measure.

10 We thank Scott Neslin for making the storability and impulse-purchase scales available to us.

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