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When Do Price Thresholds Matter in Retail Categories?

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Marketing literature has long recognized that brand price elasticity need not be monotonic and symmetric, but has yet to provide generalizable market-level insights on threshold-based price elasticity, asymmetric thresholds, and the sign and magnitude of elasticity transitions. This paper introduces smooth transition regression models to study threshold-based price elasticity of the top 4 brands across 20 fast-moving consumer good categories. Threshold-based price elasticity is found for 76% of all brands: 29% reflect historical benchmark prices, 16% reflect competitive benchmark prices, and 31% reflect both types of benchmarks. The authors demonstrate asymmetry for gains versus losses on three levels: the threshold size and the sign and the magnitude of the elasticity difference. Interestingly, they observe latitude of acceptance for gains compared to the historical benchmark, but saturation effects in most other cases. Moreover, category characteristics influence the extent and the nature of threshold-based price elasticity, while individual brand characteristics impact the size of the price thresholds. From a managerial perspective, the paper illustrates the sales, revenue, and margin implications for price changes typically observed in consumer markets.

Key words: kinked demand curve; smooth-transition regression models; time-series analysis; asymmetric price thresholds; empirical generalizations
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1. Introduction

Marketing researchers and practitioners have long acknowledged that price response functions need not be monotonic and symmetric (e.g., Gutenberg 1976, Simon 1969). Kinked demand curves (Putler 1992) imply that brand price elasticity might be subject to price benchmarks or thresholds. For example, shallow discounts might fail to generate consumer response and thus have underproportional effects on market performance compared to deep discounts (Gutenberg 1976, Hruschka 2000, Gilbride and Allenby 2004). At the same time, consumers might react strongly to even relatively minor price increases while habituation/adaptation (Kahneman 1991) leads to saturation effects for major price increases (van Heerde et al. 2001). Managerial interest in this topic is twofold: (1) to predict the sales and profit impact of different levels of price increases and decreases, and (2) to identify the category and brand characteristics that affect price elasticity thresholds (Han et al. 2001). 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. In this context, while complex threshold effects have been widely discussed (e.g., Moran 1978, Simon 1989), they have often escaped explicit modeling and empirical observation.

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, with a "latitude of acceptance" region or region of indifference such that changes in price within this region produce no changes in perception (Monroe 1990). However, their focus remained restricted to the specific behavioral phenomenon of interest: historical *or* competitive reference prices and assimilation/contrast effects *or* saturation effects (Gupta and Cooper 1992, Thaler 1985, Han et al. 2001). Second, completely data-driven approximation of the effect curve offered more flexible estimation approaches to capture a wide variety of price threshold phenomena (van Heerde et al. 2001, Kalyanam and Shively 1998). Unfortunately, this flexibility comes at the expense of severe data requirements and difficult interpretation of the parameters, especially across categories to generate guidelines for retail pricing.

Thus, while research points to the existence of brand price thresholds and kinked demand curves, the extant marketing literature lacks a large-scale econometric investigation of this phenomenon across product categories in retail markets. In particular, retail pricing managers need insights into the moderating factors of threshold-based price elasticity at the aggregate level, where they have to set prices and are accountable for the sales results. A systematic comparison across brands and categories is therefore needed to uncover empirical generalizations, to offer concrete managerial guidelines (Shugan 2003), 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 thresholds in price elasticity across a wide variety of fast-moving consumer good categories? (ii) To what extent are such deviations from constant price elasticity driven by historical versus competitive benchmark prices (hereafter HBP versus CBP)? (iii) Is there time-series evidence for asymmetric thresholds and slope changes (latitude of acceptance versus saturation effects) for gains and losses? (iv) Do these characteristics of price elasticity vary across categories and brands? We apply the methodology of logistic smooth-transition regression (STR) models (see Van Dijk et al. 2002, among others) to assess the impact of price thresholds on price elasticities.

The rest of the paper is organized as follows. In §2, we propose a research framework and hypotheses for both price discounts and price hikes on three dimensions: the nature of the benchmark (historical versus competitive), the size of the price threshold (small versus large), and the price slope difference (latitude of acceptance versus saturation effects). Next, we focus on the category and brand characteristics that might influence the presence, nature, and size of price thresholds and price elasticity differences. In §3, we discuss the econometric representation of the model we use to examine threshold-based transitions in short-run price elasticity. Section 4 describes the data and operationalization of the variables, while §5 reports the results. Finally, we formulate conclusions and future research avenues in §6.

2. Thresholds in Short-Run Price Elasticity

Over the past decade, researchers have identified thresholds in price elasticity (for a review, see Kalyanaram and Little 1994, and Raman and Bass 2002) and have called for further exploration of this issue (Bucklin and Gupta 1999, Simon 1989). Remaining issues include (1) the nature of these price thresholds or benchmarks, (2) the size of the thresholds, and (3) the sign of the change to the price elasticity. Moreover, it is not clear to what extent brand and category moderators influence these characteristics of price thresholds in retail markets. We discuss these in turn.

2.1. Characteristics of Price Thresholds

First, researchers have typically assumed that consumers use either a historical (temporal) benchmark price[1] or a competitive (contextual) benchmark price in brand choice decisions (Briesch et al. 1997). The former view argues that consumers remember the prices encountered on past purchase occasions while the latter view argues that a benchmark price is formed during the purchase occasion on the basis of the prices observed (e.g., shelf prices of competing products). This distinction in benchmark price formation is important for market-level price setting. Historical benchmark prices imply that managers should beware of own past discounting as brand price should compare favorably with past own prices, whereas competitive benchmark 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 benchmark prices find that both benchmark types matter (Kumar et al. 1998, Mayhew and Winer 1992, Rajendran and Tellis 1994, Mazumdar and Papatla 2000). Because these studies analyzed one or a few product categories, we do not yet know under which circumstances either type is more important.

Second, the observed threshold size is important for the interpretation and managerial implications of threshold-based price elasticity. Smaller thresholds, typically less than 15%, have been interpreted as an assimilation effect in consumer price perception and encoding (Kalyanaram and Winer 1995). Instead, larger thresholds could reflect intentional consumer behavior of lie in wait for even better deals (Mela et al. 1997). Moreover, threshold size could be asymmetric to gains (price decreases) versus losses (price increases) (Kalyanaram and Little 1994, Moran 1978). Recently, Han et al. (2001) found larger thresholds for gains versus losses in the coffee category. It is currently unclear whether this finding generalizes to other categories. A second asymmetry has been found for the magnitude of the elasticity difference, as consumers react more to perceived price losses than to

[1] As we analyze price thresholds at the market level, we prefer the term "benchmark price" instead of "reference price," which typically implies a reference point at the individual consumer level.

Table 1 **Conceptual Framework for Price Threshold Effects in Retail Markets**

	Negative price gap (consumer gain)	Positive price gap (consumer loss)
Amplification beyond threshold "latitude of acceptance" effects	Adaptation level theory Lie in wait for deals	Adaption level theory Differentiation
Attenuation beyond threshold "saturation" effects	Discounting of discounts Purchase limits	Discounting price hikes Core brand loyalty

price gains (Kalyanaram and Winer 1995) or vice versa (Greenleaf 1995, Krishnamurthi et al. 1992).

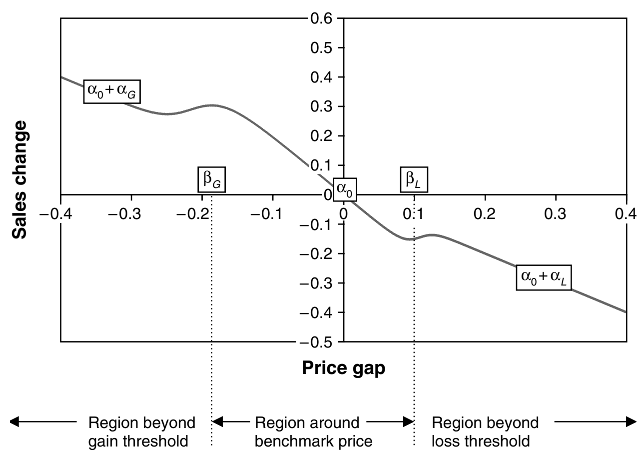
Finally, most researchers have focused on demonstrating a latitude of price acceptance, implying amplification of the price elasticity beyond a threshold (Sherif et al. 1965). In contrast, recent research has shown the possibility of saturation effects, implying attenuation of the price elasticity beyond a threshold (van Heerde et al. 2001). The distinction is crucial for pricing managers, as it implies either larger or smaller bang for the buck once the price change exceeds the threshold. Table 1 juxtaposes "latitude of acceptance" and "saturation" effects for negative price gaps (gains to the consumer; price discounts to the manager) and positive price gaps (losses to the consumer, price hikes to the manager).

Several consumer behavior theories are consistent with the four scenarios in Table 1.

- For negative price gaps (consumer gains), a latitude of acceptance is implied by adaptation level theory and assimilation-contrast theory (Kalyanaram and Little 1994, Kalwani et al. 1990): Before consumers can contrast the low price with their benchmark, the price must be perceived as different. Moreover, even when they perceive and recognize discounts, consumers may not react strongly if they are waiting for still better deals (Mela et al. 1997, Kopalle et al. 1999). Interestingly, both assimilation-contrast and "lie-in-wait" effects have been demonstrated only vis-à-vis an historical benchmark (i.e., the past price of the focal brand), not vis-à-vis competitive benchmarks.
- In contrast, saturation effects for gains are consistent with consumers engaging in "discounting of discounts" (Gupta and Cooper 1992). Intuitively, consumers do not fully consider that the price is that much lower than the benchmark and adjust their gain perception to more reasonable levels. Alternatively, saturation effects in retail markets may originate from consumer limits to purchasing, transporting, and stockpiling products (van Heerde et al. 2001). These physical limits may apply to discounts compared to both historical or competitive benchmarks.
- For positive price gaps (consumer losses), a latitude of acceptance is again consistent with adaptation level theory: A loss must also exceed a consumer's price threshold in order to be perceived. Instead, minor price hikes within the threshold are less likely to be noticed (Kalyanaram and Little 1994, Kalwani and Yim 1992).
- Saturation effects for consumer losses may represent a "discounting of price hikes," i.e., consumers may mentally adjust price increases to more "reasonable" levels. Such behavior might occur as a rationalization for buying products at higher prices, for instance, for indulgence products, or simply reflect a partial encoding of the price increase (Alba et al. 1991). Beyond perception, saturation effects are also consistent with the presence of a core loyal consumer base with a strong need or desire for the focal brand (Jacoby and Chestnut 1978). While these consumers might buy less quantity as brand price increases, they do not refrain altogether from buying the focal brand, even at very high prices.

In sum, empirical generalizations on price thresholds should consider both "latitude of acceptance" and "saturation" effects and allow for asymmetric thresholds for gains and losses. Figure 1 visualizes these different elements and provides definitions of key parameters.

Figure 1 **A Graphical Illustration of Smooth Transition Model of Price Elasticity**



Notes. Definitions: The "*base elasticity*" α_0 is the price elasticity around the benchmark price (within the price threshold). It is expected to be negative, and more negative values signify higher price sensitivity. The "*elasticity difference gain*" α_G is the elasticity change (from α_0) beyond the gain threshold. Negative (positive) values signify more (less) negative price elasticity, and thus higher (lower) price sensitivity beyond the gain threshold. The "*elasticity difference loss*" α_L is the elasticity change (from α_0) beyond the loss threshold. Positive (negative) values signify less (more) negative price elasticity, and thus lower (higher) price sensitivity beyond the loss threshold. The "*gain threshold*" β_G is the percentage change in price beyond which the price elasticity changes. As this change is relative to the benchmark price, this value is per definition negative; in this illustration, $\beta_G = -0.19$. The "*loss threshold*" β_L is the percentage change in price beyond which the price elasticity changes. As this change is relative to the benchmark price, this value is per definition positive; in this illustration, $\beta_L = 0.09$.

2.2. Moderating Role of Category and Brand Characteristics

Because managers have a keen interest in which of the identified scenarios apply under which circumstances, we develop hypotheses on the drivers of (1) the relative importance of historical versus competitive price benchmarks, (2) the price slope (elasticity difference) beyond the price threshold (latitude of acceptance versus saturation effects), and (3) the location of these benchmarks (threshold size). Prior marketing theory drives our selection of the second-stage covariates, which include category/product and brand characteristics. The former are of key interest to retailers (and multicategory manufacturers) setting pricing guidelines across categories (Shankar and Bolton 2004), while the latter are important to both retailers and brand managers.

2.2.1. Historical or Competitive Benchmarks? Latitude of Acceptance or Saturation Effects? We gauge the likelihood for historical versus competitive benchmarks by adapting the accessibility-diagnosticity framework (Feldman and Lynch 1988). In particular, the prominence of historical price benchmarks increases with (1) how likely the consumer is to remember past prices (e.g., Biehal and Chakravarti 1983), and (2) how diagnostic this memory of past prices is in predicting current/future prices (e.g., Briesch et al. 1997). We expect these drivers to also affect the price elasticity beyond the gain threshold, i.e., whether large price discounts yield higher price sensitivity[2] (latitude of acceptance) or lower price sensitivity (saturation effects).

Hypothesis 1A. *Historical benchmarks are more prominent in expensive categories.*

Expensive categories should draw greater attention to prices relative to less expensive categories purchased at the same outlet. As such, consumers are more likely to recall the price because it stands out in comparison to the prices they pay for items in less expensive categories. Therefore, historical prices in such categories should be easier to recall than in those that are less expensive. In sum, we expect that such categories are dominated by consumers who use historical benchmark prices (Mazumdar and Papatla 2000).

Hypothesis 1B. *Price elasticity beyond the gain threshold is more negative in expensive categories.*

By the same token, large price discounts on expensive products should engage more consumers than small price discounts do. Indeed, price decreases on expensive products bring them within reach for budget-conscious consumers, enabling them to enjoy quality/prestige benefits that they otherwise would not (Chandon et al. 2000). As consumers differ in terms of their reservation prices, larger discounts enable more shoppers to buy the expensive products and should thus yield more negative price elasticity than smaller discounts. Such effect is less likely for cheaper products, which most consumers are able to afford at regular prices.

Hypothesis 2A. *Historical benchmarks are more prominent in categories with low price volatility.*

The ability to remember previous prices and therefore use historical benchmarks can be influenced by the effort required to keep track of prices. The required effort would be low in categories in which prices are less volatile, and high in categories in which retail prices fluctuate due to frequent promotional activity (Mazumdar and Papatla 2000). In categories with lower price volatility, memory-based benchmark prices are more accessible and more diagnostic (Briesch et al. 1997).

Hypothesis 2B. *Price elasticity beyond the gain threshold is more negative in categories with high price volatility.*

High category price volatility typically implies a high promotional intensity, which makes shoppers accustomed to (minor) price discounts and teaches them to lie in wait for substantial price promotions (Mela et al. 1997, Kopalle et al. 1999). Therefore, we should observe a more negative price elasticity once the promotion crosses the gain threshold.

Hypothesis 3A. *Historical benchmarks are more prominent for planned purchases.*

Categories in which purchases are typically planned are those where consumers engage in 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 benchmark prices dominate (Mazumdar and Papatla 2000). In contrast, impulse buying involves reaction to contextual cues, such as the point-of-purchase prices of the product and its competitors, with little effort to retrieve relevant information from memory (Hausman 2000).

Hypothesis 3B. *Price elasticity beyond the gain threshold is more negative for planned purchases.*

Planned purchases occur for products the consumer needs, which render them less sensitive to very small price changes. Faced with huge price gains, though, consumers should feel comfortable stocking up on

[2] Throughout the paper, we use "higher" and "lower" price sensitivity as synonyms of "more negative" and "less negative" price elasticity, i.e., these terms do not signify absolute price effects on sales (Hanssens et al. 2001, p. 95).

products they planned to buy anyway. In contrast, impulse-buy products are purchased as the result of an impulsive decision, possibly triggered even by minor price gains (Chandon et al. 2000). However, large price gains are not expected to strongly impact demand: Consumers would feel reluctant to buy large quantities, as the purchase was not planned and is thus unlikely to reflect an important consumer need (Wertenbroch 1998). In case of strong price increases, some consumers would still buy the product due to strong desire. As a result, saturation effects are more likely for impulse-buy products.

Hypothesis 4. *Price elasticity beyond the gain threshold is more negative for storable products.*

A similar rationale applies for storable products, in this case concerning the opportunity of consumers to engage in strategic behavior. Small price gains are not expected to drive demand, as the nonperishable stocks at home allow consumers to lie in wait for great deals. When such great deals arrive, consumers can buy large quantities and stock them for the future.

Finally, Briesch et al. (1997) invite formal testing of two factors that may moderate the prominence of historical benchmarks: category price spread and product purchase cycle.

Hypothesis 5. *Historical benchmarks are more prominent for categories with a high price spread.*

A high price spread in the category indicates a strong degree of product differentiation, making it easier for consumers to remember prices of a specific brand. In contrast, a low price spread may confuse a consumer's memory concerning a specific brand's past prices: "Some consumers probably judged past prices as not sufficiently diagnostic to be stored in memory" (Briesch et al. 1997, p. 213).

Hypothesis 6. *Historical benchmarks are more prominent for categories with a short purchase cycle.*

Shorter purchase cycles simply make it easier for consumers to memorize prices and access this information when making a purchase (Alba et al. 1991). In the words of Briesch et al. (1997): "For some consumers, longer intervals between purchases may have caused past prices to be less readily accessible in memory and not used in price judgments" (p. 213).

In contrast to the formal hypotheses on category moderators, we do not find strong arguments for brand moderators[3] but still include those in the analysis to explore their effects.

2.2.2. Size of Thresholds for Gains and Losses. Turning to the size of the thresholds, previous literature suggests that focal cues, including price, are perceived within the behavioral situation of contextual cues such as brand familiarity (Monroe 1977), brand expensiveness, and promotional frequency of the brand and its competitors (Srinivasan et al. 2004). We discuss these moderating factors in turn.

First, brand familiarity might be due to external communication for or due to direct experience with the brand. The former is more likely for national brands versus store brands because national brands are more likely to adopt widespread advertising campaigns. The latter, consumer brand experience, is often operationalized at the market level as brand market share (Ehrenberg 1988).

Hypothesis 7. *National brands have* (a) *a lower threshold for gains but* (b) *a higher threshold for losses.*

Hypothesis 8. *High share brands have* (a) *lower threshold for gains but* (b) *a higher threshold for losses.*

As for gains, Gupta and Cooper (1992) observed that price decreases are less likely to be discounted for national brands than for store brands. Indeed, external communication engenders brand loyalty and brand preference. Therefore, the threshold for gains should be lower for national brands as consumers will react favorably to even a small gain provided by a highly reputable brand. The same reasoning applies for brand market share: Previous experience creates familiarity with the brand and yields a large consumer base to react to price gains.

As for losses, price increases on familiar brands are more likely to be tolerated than those on unfamiliar brands. Indeed, national brands invest more in communications aimed at building differentiation and consumer loyalty. Likewise, high market share provides a good indication of consumer experience with a brand (Ehrenberg 1988) and brands with a high market share are more likely to operate on the flat portion of the price-demand curve (Blattberg et al. 1995). As a result, the sales elasticity for small price hikes is likely to be lower for large-share brands versus small-share brands.

Hypothesis 9. *Expensive brands have* (a) *a lower threshold for gains but* (b) *a higher threshold for losses.*

Expensive brands enjoy an asymmetric drawing power of their promotions, as their price discounts evoke more consumer reaction (Blattberg and Wisniewski 1989). Therefore, we expect a lower threshold

[3] For one, the moderating role of brand ownership is not a priori obvious. On the one hand, store brand buyers are more likely to be price conscious and give less weight to nonprice attributes. This attention to price should enable price recall and thus lead to more use of historical benchmarks. On the other hand, store brands often invite direct comparison with competing brands (e.g., through "compare and save" tags) and are therefore more likely to be evaluated in terms of price comparisons with competitive brands at the point of purchase.

for gains for more expensive brands. As for losses, expensive brands are more differentiated due to their higher perceived quality (possibly due to branding communication), and their sales should thus be more tolerant to losses as consumers are more likely to be willing to pay for the perceived differences. Therefore, we expect a higher threshold for losses.

Hypothesis 10. *Brands with high price volatility have* (a) *a higher threshold for gains but* (b) *a lower threshold for losses*.

Turning to price volatility, frequent promotions teach consumers to lie in wait for great deals rather than purchase when only small discounts are offered (Mela et al. 1997). By the same token, even small price hikes will reduce sales as consumers are trained to wait for the next discount when brands are frequently promoted.

Hypothesis 11. *Categories with high price volatility have* (a) *a higher threshold for gains but* (b) *a lower threshold for losses*.

Likewise, in categories with high price volatility, the threshold for gains should be higher as discounts are plenty, but the threshold for losses should be smaller because consumers can easily switch to deals on competing brands.

3. Modeling Threshold-Based Price Elasticity Transitions

In this section, we discuss the econometric representation of the model we use to examine threshold-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 nonstationary 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 benchmark and "outer" regimes of gains and losses. Next, we adapt the smooth transition methodology to allow for (1) historical and competitive benchmarks, and (2) for asymmetric elasticity differences in the gains and losses regimes. Finally, we investigate whether the characteristics of threshold-based price elasticity systematically vary according to product category and brand conditions.

3.1. 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 P_t and promotion.[4] Given our interest in the price elasticity of sales, we transform the continuously measured variables sales and prices using the natural logarithm, obtaining the well-known power model (Hanssens et al. 2001). Because our weekly scanner data might show distributed lag and/or purchase reinforcement effects (Hanssens et al. 2001), it is useful to include lagged sales and prices as additional explanatory variables, resulting in the following specification:

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

where ε_t denotes a white-noise residual term. The model in Equation (1) is called an autoregressive distributed lag model of order $(1, 1)$, often denoted as ADL$(1, 1)$.[5] 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 and 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 might 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 nonstationary (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 nonstationary. A simple solution to the above problems is to rewrite Equation (1) in error-correction form (see Hendry 1995 for details):

$$\Delta \ln(S_t) = c + \alpha_0 \Delta \ln(P_t) + \alpha_2[\ln(S_{t-1}) - \alpha_3 \ln(P_{t-1})] + \varepsilon_t, \quad (2)$$

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 Equation (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

[4] Our data set lacks information on distribution and advertising, which is common for scanner data in marketing.

[5] Higher-order lags could easily be included, but the ADL$(1, 1)$ model was chosen since we found no strong evidence that higher-order dynamics would be needed for all cases. This finding is also consistent with recent VAR-based studies in which the typical number of lags for models estimated in frequently purchased consumer goods was one (e.g., Srinivasan et al. 2004, Pauwels and Srinivasan 2004).

growth in sales[6] 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. As we focus on the consistent estimation of the short-run price elasticity α_0, we guard against possible misspecification bias by including lagged levels of sales and prices, which may be evolving separately or may be cointegrated (Nijs et al. 2001, Steenkamp et al. 2004, Krider et al. 2005).[7] Likewise, prices of competing brands P_j can influence sales as may feature and display, so we include these in Equation (3):

$$\begin{aligned}\Delta \ln(S_{i,t}) &= c + \alpha_0 \Delta \ln(P_{i,t}) + \sum_{j=1}^{J-1} \kappa_j \Delta \ln(P_{j,t}) + \delta_1 FEAT_{i,t} \\ &\quad + \delta_2 DISP_{i,t} + \phi_1[\ln(S_{i,t-1}) - \phi_2 \ln(P_{i,t-1})] + \varepsilon_{i,t}, \quad (3)\end{aligned}$$

where subscript i denotes brand i.

In sum, Equation (3) allows us 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.

3.2. Incorporating Price Gap-Induced Threshold-Based Effects: Smooth Transition Models

Model (3) still assumes a constant short-run price elasticity. We therefore apply smooth-transition regression modeling as a flexible procedure that allows both for threshold-based 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 benchmark price (defined below). To that extent, we can write model (3) as

$$\begin{aligned}\Delta \ln(S_{i,t}) = c &+ [\alpha_0 + F(GAP_t)\alpha'_0]\Delta \ln(P_{i,t}) \\ &+ \sum_{j=1}^{J-1} \kappa_j \Delta \ln(P_{j,t}) + \delta_1 FEAT_{i,t} + \delta_2 DISP_{i,t} \\ &+ \phi_1[\ln(S_{i,t-1}) - \phi_2 \ln(P_{i,t-1})] + \varepsilon_{i,t}, \quad (4)\end{aligned}$$

where $F(GAP_t)$ is a continuous transition function bounded between zero and one.

Model (4) can be interpreted in two ways (Van Dijk et al. 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 zero and one. In this paper, we adopt the regime interpretation (i.e., price is either inside or outside the inner regime around a benchmark 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. The latter specification is more relevant to our research problem, as we aim to model both a lower threshold (negative price gap; consumer gain) and a higher threshold (positive price gap; consumer loss). Equation (5) displays such quadratic specification, with a lower threshold β_1 and an upper threshold β_2:

$$F(GAP_t) = \frac{1}{1 + \exp\{-\gamma(GAP_t - \beta_1)(GAP_t - \beta_2)\}}, \quad \gamma > 0. \quad (5)$$

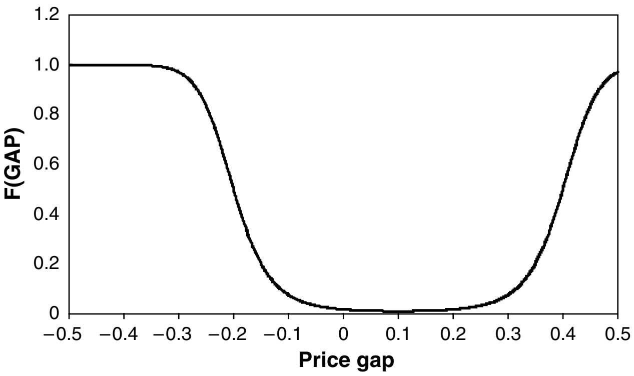
Based on our discussion of previous marketing literature, we adapt this quadratic specification by allowing for (1) asymmetric price elasticity and threshold sizes for gains and losses, and (2) different benchmarks (historical versus competitive) to define the price gap. The former phenomenon (threshold asymmetry) is incorporated by distinguishing a lower threshold β_G with elasticity change for consumer gains α_G, and an upper threshold β_L, with elasticity change for consumer losses α_L. The latter phenomenon is modeled by incorporating two transition functions: one for historical prices and one for competitive prices. Each function allows for asymmetric effects for gains versus losses. Therefore, we substitute α_0 in Equation (3) with the following expression:

$$\begin{aligned}\alpha_0 &+ \alpha_{G,HBP}(1 + \exp[\gamma(\log P_t - \log P_{t-1} - \beta_{G,HBP})])^{-1} \\ &+ \alpha_{L,HBP}(1 + \exp[-\gamma(\log P_t - \log P_{t-1} - \beta_{L,HBP})])^{-1} \\ &+ \alpha_{G,CBP}\left(1 + \exp\left[\gamma\left(\frac{P_t - \frac{1}{J-1}\sum_1^{J-1} P_t}{\frac{1}{J-1}\sum_1^{J-1} P_t} - \beta_{G,CBP}\right)\right]\right)^{-1}\end{aligned}$$

[6] This is because the first differences of logged variables are approximately growth rates.

[7] This does not apply to our specific empirical application, as none of the analyzed sales and price series is classified as evolving by (Augmented Dickey Fuller) unit root tests. We note, too, that while thresholds may also exist in long-run price elasticity, we leave this topic for future research.

Figure 2 **Transition Function for the Three-Regime Quadratic Logistic STR Model (Illustrative Example)**



$$+\alpha_{L,\,CBP}\left(1+\exp\left[-\gamma\left(\frac{P_t-\frac{1}{J-1}\sum_1^{J-1}P_t}{\frac{1}{J-1}\sum_1^{J-1}P_t}-\beta_{L,\,CBP}\right)\right]\right)^{-1}, \tag{6}$$

with α_0 the constant price elasticity in the "inner regime" $[\beta_G, \beta_L]$ around the benchmark price; α_{HBP} and α_{CBP} the additional price elasticity outside this regime for, respectively, the historical and the competitive benchmark price definition; $\beta_{G,\,HBP}, \beta_{G,\,CBP} < 0$, and $\beta_{L,\,HBP}, \beta_{L,\,CBP} > 0$ the price thresholds for, respectively, gains and losses; and parameter $\gamma > 0$ the smoothness of the transition curve. The transition is typically smooth; $\gamma \to \infty$ is a special case corresponding to an abrupt transition. Our model detects that the price difference exceeds the historical price threshold as follows (a similar rationale applies for competitive benchmark price):

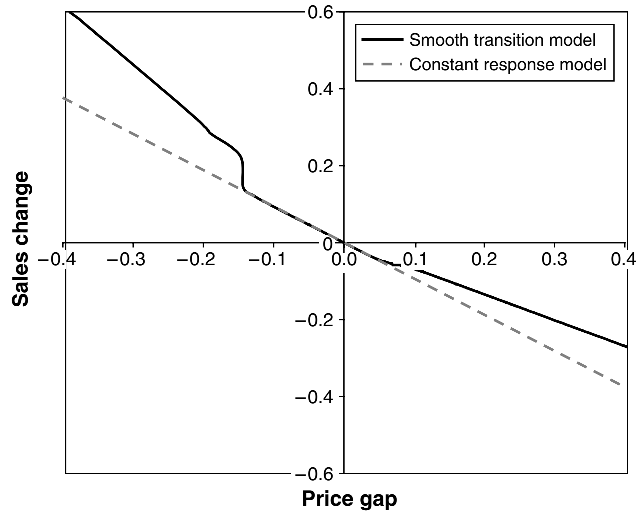
(1) The argument of the exponential function becomes zero when the price difference equals the price threshold.

(2) In contrast, when $\log P_t - \log P_{t-1} < \beta_{G,\,HBP}$, i.e., the current price represents a clear gain for consumers over the previous price, the price elasticity smoothly transitions into $\alpha_0 + \alpha_{G,\,HBP}$.

(3) Likewise, when $\log P_t - \log P_{t-1} > \beta_{L,\,HBP}$, i.e., the current price represents a clear loss over the past price, the exponential function equals one, and the price elasticity becomes $\alpha_0 + \alpha_{L,\,HBP}$.

Figure 2 visualizes the relation between the $F(GAP)$ function and the size of the price gap in a three-regime quadratic logistic STR model. For an actual brand, Figure 3 compares the predicted sales change from our model in Equation (6) with that from the constant elasticity model in Equation (3). In this case, $\alpha_{G,\,HBP} < 0$, $\alpha_{L,\,HBP} > 0$, $\beta_{G,\,HBP} = -0.16$, $\beta_{L,\,HBP} = 0.07$, and $\gamma = 50$.[8] In other words, this brand shows "latitude of acceptance" effects around the lower (gain)

Figure 3 **Change in Sales as a Function of the Gap with Historical Benchmark Price**



threshold; the negative value of $\alpha_{G,\,HBP}$ implies a higher price sensitivity below this threshold. In contrast, the positive value of $\alpha_{L,\,HBP}$ implies saturation effects, i.e., a lower price sensitivity beyond the upper threshold. Moreover, the threshold size is asymmetric as well: β_G differs from $-\beta_L$.

3.3. Model Comparison Tests for Benchmark Price Type and Threshold Asymmetry

There are several options to examine whether models with one or more transition functions are a useful way to fit the data.[9] Following Hansen (1996) and Teräsvirta (1994), we proceed as follows.[10] First, we estimate a linear model. Second, we consider an extended version of this linear model with cross products of $\Delta \ln P_t$ with $\Delta \ln P_t$, its squares and its cubes, and with cross products of this variable with the other GAP measure. Finally, we test for the relevance of the two sets of three variables using likelihood ratio (LR) tests. In case no LR test is significant, we have a linear model. In case one of the LR tests is significant, we proceed with that particular nonlinear model. If both tests are significant, we proceed with the model where α_0 is given by Equation (6).

Within the selected model for each brand, we next test for asymmetry in threshold size and elasticity

[8] These illustrative values were chosen based on our empirical estimation. We initially attempted to estimate the gamma parameters to be different. It turned out that the estimation routine each time converged to very high values of gamma, implying that the transition from one regime to the other is virtually immediate. As the estimation algorithm could not always find a sensible value, we chose to fix the gamma parameters at the same value of 500.

[9] We do not base our model selection on the AIC criterion because the AIC compares models where if one model is the true one, then strictly speaking the alternative model contains parameters that cannot be estimated. In contrast, with the LR tests, all parameters exist under the null and the alternative hypothesis.

[10] The expressions of the full and restricted models (in Eviews code) are available from the first author's website at http://mba.tuck.dartmouth.edu/pages/faculty/koen.pauwels/research.html.

difference for gains and losses. We assess this asymmetry with a binomial test for the estimated parameters $\beta_G = -\beta_L$ and $\alpha_G = \alpha_L$. Note that when the thresholds $\beta_G = -\beta_L$, our model collapses into a symmetric three-regime logistic model with a single threshold.

3.4. Comparison to Other Models with Nonconstant Price Elasticity

Evidently, the assumption of constant price elasticities has been relaxed in prior work.[11] For one, market-share attraction models (e.g., Cooper and Nakanishi 1988) imply a particular form of nonconstant elasticities and price comparison with competing brands. However, they do not allow us to investigate the nature of the price thresholds (historical versus competitive benchmarks) nor their size. Second, varying coefficient models such as the semiparametric approach in van Heerde et al. (2001) and the stochastic spline-regression approach in Kalyanam and Shively (1998) allow for a completely data-driven approximation of the effect curve to capture threshold-based effects. These approaches are extremely flexible, thereby reducing the possibility of model misspecification bias. However, their data requirements quickly become excessive and their parameters are hard to directly interpret; hence, systematic comparisons across brands and product categories, needed for the derivation of empirical generalizations and hypothesis testing, become cumbersome to implement. In comparison, we feel that our methodology is well-suited for our research goal of establishing empirical generalizations on threshold-based price elasticity across a wide range of fast-moving consumer good categories.

4. Data Description and Operationalization

The database consists of scanner records for 20 product categories from a large midwestern 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 price (appropriately deflated using the Consumer Price Index for the area), price specials, promotions, and new product introductions.[12] A maximum of 399 weeks are available for each category, from September 1989 to May 1997.[13] 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,[14] and we refer to the University of Chicago website (http://gsbwww.uchicago.edu/kilts/research/db/dominicks/) and previous papers (e.g., Srinivasan et al. 2004) for data details and summary statistics. Focusing on the top 4 brands in 20 categories, we analyze a total of 80 brands.

Table 2 details the operationalization of historical and competitive benchmark prices and second-stage moderator variables. As the historical benchmark, we use the brand-specific lagged price. Although the marketing literature has seen several competing HBP operationalizations, Kalwani et al. (1990) find little difference in fit across these alternatives. Indeed, we verified that our results are robust to using exponentially weighted lagged past prices instead of past price (Briesch et al. 1997). We operationalize the competitive benchmark price as the market share weighted average 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 et al. 1998, Rajendran and Tellis 1994). Finally, the moderator variables (consistent with previous literature) include category expensiveness, category price volatility, ability to stockpile, impulse buying, SKU proliferation, brand ownership (store versus national brand), brand market share, brand expensiveness, brand price volatility, category price spread, market concentration, and product purchase cycle. The second stage of our research assesses the hypotheses by weighted least-squares regression of the first-stage estimates on these category and brand characteristics, using as weights the inverse of the standard errors of the first-stage estimates.

5. Empirical Results

5.1. Empirical Generalizations on Threshold-Based Price Elasticity

Based on the linearity tests, the constant elasticity model is selected for 24% of all brands, while 29% demonstrate historical benchmark prices, 16% competitive benchmark prices, and 31% both (full model). Interestingly, these results partly confirm and partly extend previous research. First, we do indeed find evidence for both historical and competitive benchmarks

[11] We thank an anonymous reviewer and the area editor for these suggestions.

[12] We control for major product introductions by dummy variables in our regression.

[13] Some categories have fewer than 399 weeks of data due to missing observations.

[14] We choose to analyze price response at the brand level, given our research goal of establishing empirical generalizations across a wide range of fast-moving consumer good categories. However, we verified for the cola category that if a brand shows evidence of nonlinear price response, all its SKUs do, too.

Table 2 Variable Operationalization

Variable	Operationalization
Historical benchmark price (HBP)	Following previous research on aggregate-level data (Raman and Bass 2002, Putler 1992), we model the historical benchmark price of period t as the brand-specific price in the period $t-1$.
Competitive benchmark price (CBP)	We operationalize competitive benchmark price as the market share weighted average of the prices of all the other brands (other than the focal brand) in the category.
Category expensiveness	As with brand expensiveness, we first compute 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, e.g., Raju 1992).
Category price volatility	The category-level measure is operationalized similar to the brand price volatility, at the category level. Price at category level is the market share weighted average of prices of the brands in the category.
Ability to stockpile impulse buying	The storability and impulse-buy scales from Narasimhan et al. (1996) yield dummy variables indicating whether the product is considered perishable or storable, and whether or not it is typically associated with an impulse versus a planned purchase.
SKU proliferation	The number of SKUs in the category (Narasimhan et al. 1996) captures the extent of brand proliferation.
Brand ownership	We use a dummy variable to capture the distinction between store and national brands. This variable takes on a value of one if the brand is a store brand, and zero if it is a national brand (Srinivasan et al. 2004).
Brand market share	The brand's market share is operationalized as the average volume-based share of the brand as in Srinivasan et al. (2004).
Brand expensiveness	Following Raju (1992), we first compute 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.
Systematic brand price volatility	We compute the difference between the price in that week (P_t) and the regular price as a fraction of the regular price. The systematic volatility in price is set equal to the average of the deviation from the regular price over the data period, similar to the "variability in category sales" measure in Raju (1992).
Unsystematic brand price volatility[14]	We first obtain price shocks by estimating an autoregressive (AR) model in prices. The unsystematic volatility in prices is set equal to the average price shock as a fraction of the regular price, as in Srinivasan et al. (2004).
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).
Market concentration	We measure the category's competitive structure by market concentration, following previous work in industrial organization and marketing (Bowman and Gatignon 1995), as the sum of the shares of the top three brands in the category.
Product purchase cycle	We used the purchase cycle time measures reported by the IRI Marketing Fact book, taking the average time reported for each category over the relevant data period.

Notes. To take into account the temporal distinction between the dependent measures and the independent measures, we compute the category and brand characteristics from the first year of the data (out of five-seven years for the full data).

in price elasticity, consistent with Kumar et al. (1998), Mayhew and Winer (1992), Rajendran and Tellis (1994), and Mazumdar and Papatla (2000). However, we find that the full model (with both benchmark types) is preferred only for about one-third of the analyzed cases, whereas these authors reported it fits best for the nine categories examined. Moreover, competitive benchmark price is not more often (Hardie et al. 1993, Kumar et al. 1998) but less often (Briesch et al. 1997) the main contributor to threshold-based price elasticity. Binomial tests conclude that the price elasticity significantly differs for the inner versus outer regimes. Moreover, for historical benchmarks, we find significant differences for both the *threshold size* and the *elasticity change* for gains versus losses. Competitive benchmark thresholds show no such significant asymmetry. Table 3 presents the summary statistics of the parameter estimates (details of the linearity tests are presented in Appendix B).

Across all brands, we find that the base elasticity $\alpha_0 = -2.12$ (median -2.21, standard deviation $= 0.37$) is in line with empirical generalizations from meta-analysis (Tellis 1988, Bijmolt et al. 2005). For historical benchmark prices, the threshold size is larger for gains (23%) than for losses (15%), consistent with Han et al. (2001). Interestingly, we find increased price sensitivity for gains (-0.91), but decreased price sensitivity for losses (0.32). The former is consistent with lie-in-wait behavior for deals (e.g., Mela et al. 1997). The latter represents saturation effects for price increases, which mirror the saturation effects for price discounts reported by van Heerde et al. (2001). For competitive benchmark prices, the threshold size is about the same for gains (15%) and for losses (17%), and saturation effects emerge both for gains (0.49) and for losses (0.63). In other words, we find no latitude of acceptance compared to competitive benchmark. This is consistent with price recall studies showing that consumers could easily price rank competitors

Table 3 Summary of Key Results Across Categories (Mean and Standard Error)

	Elasticity difference gains α_G	Elasticity difference losses α_L	Gain threshold β_G	Loss threshold β_L
Historical benchmark price	−0.91 (0.40)	0.32 (0.13)	−0.23 (0.02)	0.15 (0.04)
Competitive benchmark price	0.49 (0.15)	0.63 (0.27)	−0.15 (0.03)	0.17 (0.03)

Notes. The regression results are based only on those brands with significant parameters for each type of benchmark price, i.e., $n_1 = 48$ for the historical and $n_2 = 37$ for the competitive benchmark price, out of total $n = 80$ brands. The "*elasticity difference gains*" α_G is the elasticity change (from α_0) beyond the gain threshold. Negative values signify more negative price elasticity and thus larger price sensitivity beyond the gain threshold. The "*elasticity difference losses*" α_L is the elasticity change (from α_0) beyond the loss threshold. Positive values signify less negative price elasticity and thus smaller price sensitivity beyond the loss threshold. The "*gain threshold*" β_G is the percentage change in price beyond which the price elasticity changes. As this change is relative to the reference price, this value is by definition negative. The "*loss threshold*" β_L is the percentage change in price beyond which the price elasticity changes. As this change is relative to the reference price, this value is by definition positive.

even if they did not encode exact prices (Dickson and Sawyer 1990). As competitive prices are readily observed in the store, even small deviations from competitive benchmark prices may affect focal brand sales. Instead, a price much lower than competitors might not yield a huge sales hike for several reasons, including (1) consumer associations of lower quality, and (2) the loyal consumer base for competitive brands.

5.2. Moderating Factors of Price Elasticity Transitions

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

5.2.1. Moderating Factors of Model Selection and Elasticity Difference. Table 4 reports the moderator results for the selection of the constant elasticity model (Column 2) and for the model with historical benchmark prices (Column 3). Column 4 shows the moderator results for the base elasticity α_0 and Column 5 for the elasticity difference for gains based on the historical price benchmark $\alpha_{G,HBP}$ (competitive benchmark price model selection and the other elasticity differences are not significantly affected by our moderating variables).

Column 2 shows that constant elasticity models are more often selected for categories with low price spread and low concentration, impulse-buy products,

Table 4 Category and Brand Moderators Model Selection and Price Elasticity*

	Model selection		Price elasticity***	
Variable	Constant elasticity model	Historical BP model**	Base elasticity α_0***	Elasticity difference** HBP gain $\alpha_{G,HBP}$***
Category expensiveness	0.012 (0.29)	0.026 (0.63)	**−0.145 (0.00)**	**−0.179 (0.00)**
Category price volatility	0.016 (0.20)	**−0.028 (0.03)**	**−0.247 (0.00)**	**−0.314 (0.01)**
Category price spread	**−0.267 (0.04)**	**0.356 (0.01)**	−0.808 (0.27)	**1.517 (0.09)**
Product impulse buy	**0.515 (0.00)**	**−0.041 (0.01)**	0.174 (0.85)	−0.642 (0.47)
Brand market share	0.218 (0.39)	0.060 (0.82)	**1.965 (0.02)**	1.395 (0.13)
Brand expensiveness	−0.032 (0.87)	0.049 (0.81)	−0.076 (0.91)	**−1.563 (0.07)**
Brand price volatility	**0.030 (0.03)**	−0.015 (0.29)	−0.018 (0.71)	**−0.192 (0.01)**
Market concentration	**−0.660 (0.02)**	0.385 (0.16)	**1.85 (0.05)**	**2.719 (0.01)**
Product purchase cycle	0.000 (0.96)	**−0.005 (0.03)**	−0.020 (0.13)	**0.051 (0.01)**

*Standardized coefficients (for comparability across cases) 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 at least one explained parameter; **the regression results are based on all cases (brands) for which the HBP parameters were significant ($n_1 = 48$), i.e., both HBP only ($n_3 = 23$) and HBP and CBP ($n_4 = 25$) out of a total $n = 80$ brands; and ***due to the negative sign of price elasticities α_0 and $\alpha_{G,HBP}$, a negative moderator impact signifies a more negative price elasticity, i.e., a higher price sensitivity.

Table 5 Moderating Role of Category and Brand Characteristics on Price Thresholds*

Variable	HBP gain threshold $\beta_{G,HBP}$**	HBP loss threshold $\beta_{L,HBP}$	CBP gain threshold $\beta_{G,CBP}$**	CBP loss threshold $\beta_{L,CBP}$
National brand	0.034 (0.61)	−0.101 (0.13)	**0.325 (0.00)**	0.244 (0.27)
Brand market share	**−0.274 (0.05)**	**0.363 (0.02)**	−0.189 (0.23)	−0.347 (0.26)
Brand expensiveness	−0.035 (0.68)	0.022 (0.87)	**0.067 (0.00)**	**0.099 (0.05)**
Brand price volatility	0.008 (0.21)	**−0.010 (0.04)**	**−0.042 (0.00)**	**−0.029 (0.04)**
Category price volatility	−0.025 (0.19)	0.003 (0.87)	**0.026 (0.05)**	**−0.023 (0.06)**

*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 at least one explained parameter. All regression results are based only on those brands with significant parameters for each type of benchmark price, i.e., $n_1 = 48$ for the historical and $n_2 = 37$ for the competitive benchmark price out of total $n = 80$ brands; **due to the negative sign of gain thresholds $\beta_{G,HBP}$ and $\beta_{G,CBP}$, a negative moderator impact signifies a higher gain threshold.

and brands with high price volatility. In contrast, Column 3 demonstrates that historical benchmark prices more often play a role for categories with low price volatility and high price spread, and for planned purchase products with a short purchase cycle, in support of hypotheses Hypothesis 2A, Hypothesis 3A, Hypothesis 5, and Hypothesis 6. These findings corroborate the arguments in Briesch et al. (1997): Consumers' recall of past brand prices is better and more predictive of current prices if they are frequently exposed to prices that do not change often, that strongly differ from competing brands, and that are related to planned purchases.

As the current price represents a gain over the historical benchmark price (Column 5 in Table 4), the price elasticity is more negative in expensive categories (Hypothesis 1B) and in categories with high price volatility (Hypothesis 2B). Interestingly, we observe similar effects for the brand moderators: Expensive brands with high price volatility[15] experience higher consumer response once the gain threshold is crossed. Both effects are consistent with our arguments for the category-level moderators: Substantial price discounts allow more budget-conscious consumers to buy expensive brands and "shock" consumers out of their lie-in-wait game for brands with high price volatility. Finally, products with a long purchase cycle face a more constant price promotional elasticity when bridging the gain threshold, as do concentrated categories with a high price spread (Narasimhan et al. 1996). The former result is consistent with the above rationale and the finding that historical benchmarks matter less for products with long purchase cycles. The latter results are consistent with "monopolistic competition" conditions (Mas-Colell et al. 1995): Highly differentiated brands in concentrated categories face lower consumer price sensitivity.

5.2.2. Moderating Factors Relating to Threshold Size. Table 5 presents the moderator results for threshold size. First, based on the historical benchmark price (Columns 2–3), high-share brands have a larger threshold for gains and losses (in support of Hypothesis 7B). This result 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 loss threshold is lower for brands with high price volatility, in support of Hypothesis 10B. In other words, saturation effects of price hikes set in later for brands that teach consumers to buy on deal (Mela et al. 1997).

[15] We report the estimates for systematic brand price volatility, as we obtain similar results for unsystematic volatility (Leeflang and Wittink 2001), measured as the residual shocks from an autoregressive model in prices. The high correlation between these two measures prevents us from assessing their separate effects in one model.

For competitive benchmark prices (Columns 4–5 in Table 5), national brands have lower thresholds for gains, in support of Hypothesis 7A. Moreover, expensive brands have a lower threshold for gains and a higher threshold for losses (Hypotheses 9A, B). In contrast, brands with high price volatility have higher thresholds for gains and lower thresholds for losses (Hypotheses 10A, B). Finally, both the gain and loss thresholds are lower in categories with high price volatility, in support of Hypothesis 11B, but opposite to Hypothesis 11A. Table 6 summarizes our hypotheses and findings.

5.3. Managerial Relevance of Price Thresholds

To illustrate the managerial relevance of price elasticity transitions, we report and contrast the price impact on performance under constant elasticity versus under threshold-based price elasticity. For this illustrative purpose, we select two different brands in the toothpaste category, showing evidence for historical and competitive benchmark prices, respectively, and with typical parameter estimates (detailed estimates are provided in Appendix A). Figures 3 and 4 compare the constant elasticity with the threshold-based price elasticity for these brands.

Figure 3 illustrates how the price sensitivity increases once the historical benchmark 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 16% discount versus the losses threshold at 7% increase over the benchmark price. In managerial terms, the brand obtains more bang for the buck with, e.g., a 20% promotion than with a 10% promotion.[16] The opposite implication applies for price increases: One 10% price increase yields less % sales loss than two price increases of 5%. In contrast, Figure 4 shows saturation effects for both gains and losses over the competitive benchmark price: The price sensitivity decreases once the gain of 16% and loss threshold of 17% are crossed. Next, we calculate the effect of four "typical" price changes (based on their pricing history: 5%, 10%, 20%, and 25%) on (a) unit sales, (b) revenues (sales∗retail price), and (c) retailer gross margin (sales ∗ unit margin).

Table 7 shows that a 5% price change leads to identical sales, retailer revenue, and retailer margin response for both the historical benchmark price model and the constant elasticity model. Indeed, this price change is below the threshold for both gains and losses. For a 10% price change, the constant elasticity model estimates diverge from our model estimates

[16] However, managers should beware that such discounts may lower the benchmark price and thus the effectiveness of future price promotions (Kopalle et al. 1999).

Table 6 Summary of Hypotheses and Findings

	Hypothesis	Supported?
Hypothesis 1A	Historical benchmarks are more prominent in *expensive categories*.	No
Hypothesis 1B	Price elasticity beyond gain threshold is more negative in *expensive categories*.	Yes
Hypothesis 2A	Historical benchmarks are more prominent in *categories with low price volatility*.	Yes
Hypothesis 2B	Price elasticity beyond gain threshold is more negative in *categories with high price volatility*.	Yes
Hypothesis 3A	Historical benchmarks are more prominent for *planned* purchases.	Yes
Hypothesis 3B	Price elasticity beyond gain threshold is more negative for *planned* purchases.	No
Hypothesis 4	Price elasticity beyond gain threshold is more negative for *storable* products.	No
Hypothesis 5	Historical benchmarks are more prominent in *categories with high price spread*.	Yes
Hypothesis 6	Historical benchmarks are more prominent in *categories with short purchase cycle*.	Yes
Hypothesis 7A	*National brands* have a lower threshold for gains.	Yes
Hypothesis 7B	*National brands* have a higher threshold for losses.	No
Hypothesis 8A	*High-share brands* have a lower threshold for gains.	No
Hypothesis 8B	*High-share brands* have a higher threshold for losses.	Yes
Hypothesis 9A	*Expensive brands* have a lower threshold for gains.	Yes
Hypothesis 9B	*Expensive brands* have a higher threshold for losses.	Yes
Hypothesis 10A	*Brands with high price volatility* have a higher threshold for gains.	Yes
Hypothesis 10B	*Brands with high price volatility* have a lower threshold for losses.	Yes
Hypothesis 11A	*Categories with high price volatility* have a higher threshold for gains.	No
Hypothesis 11B	*Categories with high price volatility* have a lower threshold for losses.	Yes

for price increases (overestimating price response by 40%) but not for price decreases. Finally, a 20% 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 20% price discounts is 65% higher when the historical benchmark price effect is considered. Knowledge of such benchmark-based price thresholds is thus important to brand manufacturers, which have considerable control over their brand pricing policies given rather high retailer pass-through rates (Besanko et al. 2005). Interestingly, the impact of benchmark prices on retailer revenue and gross margin effect estimates are even stronger. Most notably, a 25% price hike decreases profit performance by 40% more under constant elasticity versus the HBP model. This difference between the two models is important, since not accounting for the appropriate sales response to prices can lead to suboptimal pricing decisions and hence lower profits.

For the competitive benchmark price definition, Table 8 shows that a 5% price change yields identical performance response for both the constant elasticity and the competitive benchmark price model. In other words, brand managers should beware that even small differences with competitive prices engage consumer response. Given the higher thresholds, even a 10% price change has similar effects for both models. In contrast, price changes of 25% result in

Figure 4 Change in Sales as a Function of the Gap with Competitive Benchmark Price

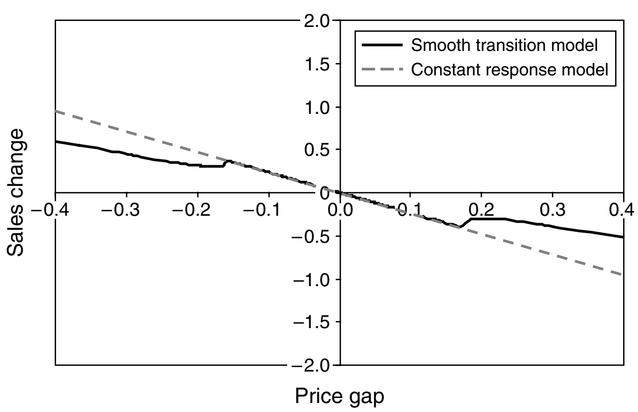


Table 7 Performance Response Based on Historical Benchmark Price of Toothpaste Brand 2

	Price promotion		Price increase	
	Smooth transition	Constant elasticity	Smooth transition	Constant elasticity
Sales response (in 1,000s)				
5% price change	310	310	−330	−330
10% price change	640	640	−460	−640
20% price change	2,120	1,290	−920	−1,280
25% price change	2,640	1,600	−1,150	−1,590
Retailer revenue response (in $K)				
5% price change	1,110	1,110	−1,220	−1,220
10% price change	2,260	2,260	−1,720	−2,390
20% price change	7,280	4,430	−3,530	−4,920
25% price change	8,940	5,420	−4,470	−6,190
Retailer gross margin response (in $K)				
5% price change	280	280	−305	−305
10% price change	570	570	−430	−600
20% price change	1,820	1,110	−880	−1,230
25% price change	2,240	1,360	−1,120	−1,550

Table 8 Performance Response Based on Competitive Benchmark Price of Toothpaste Brand 4

	Price promotion		Price increase	
	Smooth transition	Constant elasticity	Smooth transition	Constant elasticity
Sales response (in 1,000s)				
5% price change	880	880	−940	−940
10% price change	1,810	1,810	−1,850	−1,850
20% price change	2,430	3,680	−2,290	−3,630
25% price change	3,080	4,880	−2,560	−4,570
Retailer revenue response (in $K)				
5% price change	2,830	2,830	−3,120	−3,120
10% price change	5,720	5,720	−6,230	−6,230
20% price change	7,430	11,250	−7,930	−12,580
25% price change	9,200	14,590	−9,000	−16,070
Retailer gross margin response (in $K)				
5% price change	710	710	−780	−780
10% price change	1,430	1,430	−1,560	−1,560
20% price change	1,860	2,810	−1,980	−3,150
25% price change	2,300	3,650	−2,250	−4,020

considerably lower sales response due to CBP-based saturation effects. The overestimation of sales effects by the constant elasticity model is 35% for gains and 45% for losses. Note that, though the threshold sizes are similar, the saturation effects are higher for losses versus gains. Again, retailer revenue and gross margin implications are in line with the sales implications but have a higher magnitude. These results are particularly relevant as retailers set prices for all competing brands and thus may influence competitive benchmark price directly by choosing either negative or positive cross-brand pass through (Besanko et al. 2005). When the retailer acts to maximize brand-related profits, as observed by Pauwels (2007), 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 underestimates the performance impact of large discounts over historical benchmark prices, and substantially overestimates the performance impact of large increases over historical benchmark prices and of price changes vis-à-vis competitive benchmark prices. Therefore, it is important for managers to account for assimilation/contrast effects and saturation effects, particularly once the threshold is crossed.

6. Conclusions and Future Research Directions

This study applied the methodology of smooth transition models to investigate the evidence for threshold-based price elasticity across a wide range of fast-moving consumer good categories. Based on our analysis of the top 4 brands in 20 retail categories, we find that 29% demonstrate historical benchmark prices, 16% competitive benchmark prices, and 31% both. Therefore, we conclude that *price thresholds do matter for the majority of the analyzed brands and categories*. Moreover, in the case of historical benchmarks, we find evidence for *asymmetric thresholds*, and for *different sign and magnitude* of elasticity transitions, signaling the need to consider a broad framework of threshold-based price elasticities. For historical benchmark prices, the threshold size is larger for gains (23%) than for losses (15%) and the assimilation/contrast effects for gains (−0.91) are larger than the saturation effects for losses (0.32). For competitive benchmark prices, the threshold size is similar for gains (15%) and losses (17%), and saturation effects emerge both for gains (0.49) and for losses (0.63).

Finally, the second-stage analysis reveals the moderating role of both category and brand characteristics. As expected, category/product characteristics drive the basic dimensions of nonlinear price elasticity (nature of reference and kind of effects beyond the threshold), while brand characteristics influence the threshold location. Specifically, historical benchmark prices more often play a role for planned purchases and in categories with low price volatility, high purchase frequency, and high price spread. Beyond the historical gain threshold, price sensitivity increases more for categories and brands that are expensive and have volatile prices. In contrast, concentrated markets with long purchase cycles do not experience a strong increase in price sensitivity beyond the historical gain threshold. When price discounting, high-share brands face larger latitude of acceptance while concentrated markets show smaller latitude of acceptance. When raising prices, saturation effects set in later for high-share brands with low price volatility. As for competitive benchmark prices, saturation effects set in later for expensive brands with low price volatility and in categories with low price volatility. Most of these findings are consistent with the developed hypotheses based on previous marketing literature.

The managerial relevance of our findings is illustrated for two representative brands in the toothpaste category. Price changes of 5% yield similar performance effects for the constant elasticity and the benchmark price models, as all threshold sizes exceed 5%. 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 underestimates the performance impact of large discounts over historical benchmark prices, and substantially overestimates the performance impact in all other cases. In other words, the smooth transition model captures both strong and subtle threshold-based performance response near the asymmetric threshold for gains and losses.

This study has several limitations which provide promising areas for future research. First, our empirical evidence is based on data for one chain in one geographical market. Therefore, further studies are needed to determine whether our findings apply to different retail settings and whether incorporating competing retailers' prices matters. Second, 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. Third, we did not model the role of feature and display on benchmark price elasticity. Likewise, richer data sets would allow us to account for threshold-based response to changes in other marketing-mix variables such as advertising. Fourth, our model could be expanded by allowing for more than three regimes of threshold-based elasticity. This extension would allow empirical assessment of the doubly kinked price response curve (Gutenberg 1976, Hruschka 2000). Fifth, our modeling approach can be used to investigate threshold-based market share response (rather than sales response). Sixth, the estimation of thresholds in long-run price elasticity, and of including potential long-run relationships among competing prices, remain challenging areas for future research. Moreover, future research could allow for nonconstant relations between the price elasticities and the price thresholds and the second-stage characteristics as well as the potential endogeneity of these characteristics. Seventh, while the focus of the present study is on brand-level pricing issues, future research could address SKU-level pricing. Finally, analysis at the individual-consumer level is needed to validate suggested explanations of the observed threshold-based elasticities at the market level. In particular, such research can provide the basis for classifying threshold sizes, can incorporate storage effects directly, and can distinguish adaptation level from lie-in-wait effects and "discounting of discounts" from purchase limit perceptions.

Fine-tuning prices requires deeper knowledge of threshold-based price elasticity, 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 benchmark prices and of asymmetry for gains versus losses on three levels: the threshold size and the sign and the magnitude of the elasticity difference. Moreover, the specifics of threshold-based price elasticity 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 benchmark price to either reduce the sales impact of price increases or enhance brand sales response to price discounts. Together with research on dynamic pricing effects, such knowledge enables the move toward an optimization model for retail price fine tuning across brands and categories.

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Appendix A
Table A.1 provides diagnostic measures on the model fit. Specifically, we report the *R*-squared values for the constant model and for the threshold-based model, if the latter is selected. In addition, we tested the models for residual autocorrelation, for ARCH, and for normality as outlined in Eitrheim and Teräsvirta (1996) and Teräsvirta (1998). For illustrative purposes, Table A.2 provides estimation results for the toothpaste category. Specifically, we report the model and the parameter values with the standard errors.

Table A.1 **Comparison of *R*-Squared for Threshold-Based vs. Constant Elasticity Model**

Category	Brand	Type of threshold model	Threshold model fit	Constant model fit
Analgesics	2	HBP and CBP	0.594	0.531
	3	HBP and CBP	0.483	0.355
Bottled juice	2	HBP and CBP	0.735	0.714
	3	HBP	0.794	0.787
Cheese	1	HBP and CBP	0.828	0.798
	3	HBP	0.738	0.715
	4	HBP	0.827	0.817
Cookies	2	HBP	0.784	0.759
	3	HBP	0.428	0.425
Crackers	1	HBP	0.770	0.763
	2	HBP	0.903	0.897
	4	HBP and CBP	0.768	0.720
Canned soup	1	HBP and CBP	0.703	0.673
	2	CBP	0.405	0.396
	3	HBP and CBP	0.615	0.576
	4	HBP and CBP	0.832	0.810
Frozen dinner	1	HBP	0.866	0.862
	2	HBP and CBP	0.944	0.928
	3	HBP and CBP	0.900	0.863
	4	HBP	0.908	0.892
Frozen juice	1	HBP	0.897	0.863
	2	CBP	0.645	0.609
	3	HBP and CBP	0.791	0.758
	4	HBP	0.835	0.820

Table A.1 Continued

Fabric softener	1	HBP and CBP	0.693	0.620
	3	HBP and CBP	0.602	0.552
Laundry detergent	1	HBP	0.855	0.847
	2	CBP	0.768	0.753
	4	CBP	0.780	0.758
Paper towels	1	HBP	0.868	0.864
	2	HBP and CBP	0.863	0.852
	4	HBP and CBP	0.788	0.777
Refrigerated juice	1	HBP	0.818	0.803
	2	HBP	0.900	0.893
	3	CBP	0.781	0.752
	4	HBP	0.836	0.818
Soft drinks	2	CBP	0.808	0.766
	3	HBP	0.896	0.880
	4	HBP and CBP	0.794	0.720
Shampoo	2	HBP	0.914	0.902
	4	HBP	0.920	0.902
Soaps	1	CBP	0.842	0.821
	2	CBP	0.836	0.774
Toothbrush	2	CBP	0.701	0.684
	4	HBP and CBP	0.599	0.490
Toothpaste	1	HBP	0.780	0.770
	2	HBP	0.782	0.776
	4	CBP	0.807	0.788
Toilet tissue	1	HBP and CBP	0.927	0.913
	2	HBP and CBP	0.872	0.826
	3	HBP	0.722	0.690
	4	HBP and CBP	0.653	0.540
Tuna	1	CBP	0.727	0.724
	2	CBP	0.858	0.848
	3	HBP and CBP	0.870	0.861

Table A.2 Smooth Transition Model Estimation Results for the Toothpaste Category (Standard Errors in Parentheses)

Category	Brand	Model	α_0	α_G	α_L	β_G	β_L
Toothpaste	2	HBP	−0.934	−0.609	0.262	−0.164	0.067
			(0.207)	(0.163)	(0.156)	(0.090)	(0.032)
Toothpaste	4	CBP	−2.358)	0.876	1.054	−0.157	0.171
			(0.305)	(0.287)	(0.277)	(0.021)	(0.020)

Appendix B

In this technical appendix, we report details on the tests for nonlinearity at the brand level.

Table B.1 Test Results for Nonlinearity at the Brand Level (p Values of Test Statistics)

Category	Brand	HBP, CBP	HBP	CBP	Decision
Analgesics	1	0.6704	0.8460	0.6330	Linear
	2	0.0000	0.0002	0.0000	HBP and CBP
	3	0.0000	0.0000	0.0000	HBP and CBP
	4	0.4336	0.3304	0.1212	Linear
Bottled juice	1	0.0259	0.1179	0.6126	Linear
	2	0.0000	0.0332	0.0459	HBP and CBP
	3	0.0040	0.0063	0.0791	HBP
	4	0.0621	0.9846	0.0935	Linear
Cereal	1	0.1217	0.2273	0.8339	Linear
	2	0.3897	0.6309	0.2620	Linear
	3	0.1383	0.1498	0.4689	Linear
	4	0.1540	0.4934	0.7802	Linear
Cheese	1	0.0000	0.0000	0.0001	HBP and CBP
	2	0.0000	0.0000	0.0000	HBP and CBP
	3	0.0001	0.0191	0.4421	HBP
	4	0.0102	0.0009	0.1270	HBP
Cookies	1	0.2777	0.4668	0.4191	Linear
	2	0.0012	0.0206	0.5775	HBP
	3	0.0037	0.0341	0.0799	HBP
	4	0.2498	0.5529	0.1948	Linear
Crackers	1	0.0111	0.0028	0.3377	HBP
	2	0.0077	0.0127	0.1202	HBP
	3	0.0000	0.1346	0.0004	CBP
	4	0.0000	0.0000	0.0000	HBP and CBP
Canned soup	1	0.0006	0.0044	0.0038	HBP and CBP
	2	0.0382	0.0772	0.0309	CBP
	3	0.0000	0.0000	0.0002	HBP and CBP
	4	0.0000	0.0000	0.0050	HBP and CBP
Frozen dinner	1	0.0215	0.0215	0.1280	HBP
	2	0.0000	0.0000	0.0005	HBP and CBP
	3	0.0000	0.0000	0.0000	HBP and CBP
	4	0.0001	0.0000	0.3538	HBP
Frozen juice	1	0.0000	0.0000	0.4005	HBP
	2	0.0000	0.1343	0.0008	CBP
	3	0.0000	0.0000	0.0004	HBP and CBP
	4	0.0000	0.0013	0.3362	HBP
Fabric softeners	1	0.0000	0.0010	0.0000	HBP and CBP
	2	0.0249	0.0894	0.9070	Linear
	3	0.0000	0.0000	0.0143	HBP and CBP
	4	0.0000	0.0000	0.4432	HBP
Laundry detergent	1	0.0137	0.0027	0.6677	HBP
	2	0.0007	0.2856	0.0004	CBP
	3	0.0197	0.1569	0.2955	Linear
	4	0.0000	0.2209	0.0000	CBP
Paper towels	1	0.0143	0.0033	0.1104	HBP
	2	0.0000	0.0000	0.0000	HBP and CBP
	3	0.0408	0.2363	0.3959	Linear
	4	0.0000	0.0073	0.0001	HBP and CBP
Refrigerated juice	1	0.0019	0.0002	0.4038	HBP
	2	0.0000	0.0000	0.8613	HBP
	3	0.0000	0.3212	0.0021	CBP
	4	0.0001	0.0013	0.4759	HBP
Soft drinks	1	0.4714	0.3602	0.6591	Linear
	2	0.0000	0.3424	0.0003	CBP
	3	0.0001	0.0000	0.0836	HBP
	4	0.0000	0.0000	0.0010	HBP and CBP
Shampoo	1	0.0022	0.0001	0.0101	HBP and CBP
	2	0.0655	0.0085	0.5021	HBP
	3	0.0007	0.0004	0.0002	HBP and CBP
	4	0.0000	0.0000	0.2509	HBP
Soap	1	0.0000	0.8392	0.0003	CBP
	2	0.0000	0.1629	0.0000	CBP
	3	0.6494	0.4768	0.4279	Linear
	4	0.0000	0.0038	0.0000	HBP and CBP
Toothbrush	1	0.7965	0.9901	0.4243	Linear
	2	0.0106	0.2405	0.0236	CBP
	3	0.3395	0.9404	0.1010	Linear
	4	0.0000	0.0224	0.0000	HBP and CBP

Table B.1 Continued

Category	Brand	HBP, CBP	HBP	CBP	Decision
Toothpaste	1	0.0010	0.0014	0.6260	HBP
	2	0.0321	0.0206	0.4955	HBP
	3	0.3345	0.1528	0.7386	Linear
	4	0.0000	0.2270	0.0018	CBP
Toilet tissue	1	0.0000	0.0009	0.0399	HBP and CBP
	2	0.0000	0.0058	0.0000	HBP and CBP
	3	0.0000	0.0050	0.1968	HBP
	4	0.0000	0.0000	0.0000	HBP and CBP
Tuna	1	0.0001	0.2175	0.0001	CBP
	2	0.0008	0.2571	0.0120	CBP
	3	0.0000	0.0060	0.0000	HBP and CBP
	4	0.1108	0.4892	0.4140	Linear

Note. The decision rule is as follows: If the p value is smaller than 0.05 for both HBP and CBP, then the decision is "HBP and CBP." If the p value is larger for one of these, then the decision is either "HBP" or "CBP." If both are larger, then the decision is the "linear" model.

REMARK. Due to multicollinearity, it can happen that the joint tests for HBP and CBP are significant, while they are not individually. Also, for the same reasons, the joint test can be insignificant, while the separate tests are significant.

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