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In studying retailer pricing behavior, researchers typically assume that retailers maximize profits across all brands in a focal product category. In this article, the author attempts to study empirically the extent to which three factors affect retail prices: (1) the effects of payments from manufacturers to the retailer other than regular promotions, as well as the effects of additional costs borne by the retailer for these brands; (2) the retailer's objectives specific to its store brand, such as maximizing store brand share; and (3) the effects of retail competition and store traffic. By specifying a demand function at the brand-chain level for each brand in the product category, the author derives pricing rules for the retailer. The author decomposes the retail price of a brand into effects due to wholesale price, markup (obtained from the demand functions), additional promotional payments, retail competition, and the retailer's objectives for the store brand. The author carries out empirical analysis for a specific product category at a single retail grocery chain. The results indicate that the effects of the three factors vary across brands in the category.

Investigating Category Pricing Behavior at a Retail Chain

Studying retailer pricing behavior is an issue that has generated a great deal of interest in the marketing literature. Researchers have examined the issue from both theoretical (e.g., Choi 1991; Raju, Sethuraman, and Dhar 1995) and empirical (e.g., Tellis and Zufryden 1995) perspectives. Most studies assume that retailers set prices for different brands in a product category to maximize total category profits (see, e.g., Raju, Sethuraman, and Dhar 1995; Tellis and Zufryden 1995; Vilcassim and Chintagunta 1995). Although some recent studies have advocated examining profits across categories, the idea of maximizing profits at the category level appears to be the basis of most studies on retail pricing behavior. This objective is also consistent with the move toward category management as a way of doing business for both manufacturers and retailers (see, e.g., Zenor 1994).

The theoretical literature on retail pricing (see Lal, Little, and Villas-Boas 1996; Lal and Villas-Boas 1998; Pesendorfer 2001) discusses several factors that determine a retailer's price for a brand in a given week, at least for frequently purchased items such as those considered in this study. Two key drivers of these prices are (1) manufacturers' actions (e.g., wholesale prices, promotional payments) and (2) retail competition. However, most of the empirical literature on retailer pricing has focused on only one of these decisions. For example, Tellis and Zufryden (1995) assume values for wholesale prices and then examine the effects of manufacturers' actions on retail prices. Although Pesendorfer (2001) accommodates both factors in his theoretical formulation, the data he uses do not contain information on wholesale prices.

In this article, I incorporate both of these factors that affect retailer pricing into a single empirical analysis. Thus, I build on the previous empirical literature on retailer pricing behavior (Gupta 1993; Kim, Blattberg, and Rossi 1995; Tellis and Zufryden 1995; Vilcassim and Chintagunta 1995; Zenor 1994). Whereas most previous research has focused on the prices the retailer should charge conditional on the estimated demand function parameters, my objective is to analyze whether observed retail prices reflect factors suggested in the literature. In carrying out this analysis, I also account for some additional empirical issues that arise because of the nature of the data at hand. I discuss these issues that could affect retailer pricing behavior in the context of the data available for the empirical analysis.

The data are for one of two chains in a market dominated by these two grocery chains. At the chain level, for a partic-

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ular product category, the data are weekly retail prices, sales (quantities), and promotions. In addition, the data contain the number of shoppers who visit the chain each week (i.e., store traffic), the population of the market area covered by all the stores in the chain, and the retailer's weekly markups (retail prices less wholesale prices paid to the manufacturer). The wholesale prices are the net of trade promotions such as off-invoice discounts and promotional moneys for feature advertisements and special displays for that category. This helps account for wholesale price levels in the analysis of retail prices.

The reported wholesale prices, however, do not include other promotional payments made by the manufacturer to the retailer (Dreze and Bell 2000; Hauser, Simester, and Wernerfelt 1997; Lariviere and Padmanabhan 1997). For example, companies like Procter & Gamble have established brand development funds for their resellers (*Advertising Age* 1992). The size of this fund for a particular retailer reflects the revenues generated by that retailer across all Procter & Gamble products sold in its stores. Similar to brand development funds is "street money" (Blattberg and Neslin 1990, p. 319), which is "lump sum payments by manufacturers to retailers based on the amount of promotional support offered by the retailer." Payments such as development funds and street money influence the pricing policies of the retail chain and must be accounted for (Blattberg and Neslin 1990; Kim and Staelin 1999). As noted in *Advertising Age* (1992, p. 1), such funds "will encourage supermarkets to promote P&G brands consistently in ads and in the store to increase consumer demand." A recent study by Cannondale Associates, which specializes in trade promotion consulting, provides the percentage breakdown of trade promotion dollars shown in Table 1 (*Frozen Food Age* 2000).

Table 1 indicates that off-invoice discounts are the most important component of manufacturers' trade promotion expenditures. However, discretionary funds and other payments make up approximately 40% of the pie. (Billbacks have recently become popular but did not constitute a significant fraction of expenditures during the period of the data analyzed.) These funds can be used by retailers to pay for features and displays but can also be passed along as price reductions to consumers. Cannondale Associates' study indicates that approximately 60% of all promotional dollars are passed along to consumers. Therefore, to the extent that such promotional payments are reflected in the prices charged by retailers, they need to be accounted for in the analysis. It is expected that the higher the pass-through of such promotional payments for a brand, the lower is its retail price.

Although promotional payments have the effect of potentially lowering the retail price, the chain might incur additional costs for each of the brands (e.g., reallocation of shelf space to accommodate a special pack) that could increase that price. Borrin and Farris (1990) discuss several of these costs that drive the profitability of a brand. From a research perspective, it would be of interest to determine the influence of the additional promotional payments as well as costs on the retailer's pricing of products in a particular category. The key challenge in doing so stems from such payments and costs being unobserved in the data. Consequently, an empirical methodology would be needed that can estimate these from the data and then understand their effects on the retailer's pricing behavior. I discuss such a methodology in this article.

In the following, I refer to the net value of the promotional payments described previously and other costs as "side payments." As I explain subsequently, the reason for examining only the net effect is that given the available data, the promotional payments cannot be empirically separated out from the costs, but the implications of the net effect on retail prices can be obtained. The term "side payments" is chosen for convenience and denotes payments (and costs) that are not observed. Hauser, Simester, and Wernerfelt (1997) note that side payments are prevalent in vertical interactions between an upstream agent (in this case, the manufacturer) and a downstream agent (the retailer). They define (p. 246) side payments as being "known politely as gainsharing and pejoratively as bribery." Although payments such as brand development funds have not been deemed illegal, smaller retailers complain that they discriminate in favor of larger resellers. Kim and Staelin (1999) provide a theoretical analysis of side payments and analyze the extent of pass-through of such payments to the end consumer.

Returning to the two factors driving retail prices mentioned previously, with the wholesale prices observed in the data and the unobserved promotional payments that are estimated from the data, the impact of manufacturers' actions on retail prices can be accounted for. The other key driver of a retailer's price-setting behavior is retail competition. Retailers typically react to promotional activities at competing chains by running their own promotions and attracting store traffic. Store traffic in a given week refers to the number of shoppers who visit the store in that week. A vast literature in marketing suggests that retailers lower the prices of national brands to attract shoppers into the store (Dhar and Hoch 1997; Dreze 1995). The empirical evidence that relates prices and promotions in certain categories to store traffic is mixed, however. Whereas Dreze (1995) finds that lower prices in the cola category attract more shoppers into the store, studies by Walters and his coauthors find otherwise (Walters 1991; Walters and MacKenzie 1988; Walters and Rinne 1986).

One way of studying retail competition would be to study the impact of promotions at competing retailers in a given week on the prices at the chain under consideration in subsequent weeks. However, those data are not available. Therefore, I use a proxy for the effects of retail competition. Recall that the available data are for store traffic for the focal chain. Promotional activities by a competitor in a given week could lower traffic at the chain in that week, so responding to retail competition would be akin to responding to a lower store traffic level at the chain being analyzed. Therefore, to study the effects of retail competition, I ask the

Table 1
BREAKDOWN OF TRADE PROMOTION DOLLARS

Percentage of Dollars Allocated to …	*1998–99*	*1999–2000*
Discretionary funds	36	28
Off-invoice discounts	33	32
Billbacks	22	29
Slotting allowances, new item fees, and other unspecified expenditures	9	11

equivalent question: Does a lower traffic number in a given week trigger a price response in a given category during subsequent weeks? By providing an answer to this question, the article sheds some light on the extent to which retail competition that drives store traffic influences the retailer's pricing of brands within a particular product category of interest.

Accounting for manufacturer actions and retail competition enables me to build a model to study their effects on retail prices. However, there is one other complication that arises because of the nature of the data available. This stems from the category containing not only national brands but also the retailer's own brand or store brand. As several authors have pointed out, the store brand plays an important strategic role for the retailer (see Dhar and Hoch 1997; Hoch and Bannerji 1995; Narasimhan and Wilcox 1998; Scott-Morton and Zettelmeyer 2000). Dhar and Hoch (1997) note that retailers are interested in enhancing the performance of store brands in terms of market share, because a successful private label program for a store or chain builds customer loyalty for the retailer. Furthermore, there is the "umbrella branding" effect (the same name across product categories) of the private label (Scott-Morton and Zettelmeyer 2000). In other words, purchase and a positive experience in one category may motivate the consumer to purchase the store brand in other product categories as well. Therefore, although the retailer's primary objective may be to maximize category profits, it may also be interested in maximizing the share of the store brand within that category. I account for these two objectives for the retailer and attempt to empirically disentangle the relative importance of these objectives in the retailer's price-setting behavior within a product category.

I explicitly consider the effects of three factors—manufacturer actions, retail competition or store traffic considerations, and store brand objectives—on retail prices, and I determine the retailer's pricing "rules." I then estimate the parameters of these pricing rules using data for a specific product category from a single chain. This study provides some insights into the factors that drive retailer behavior, subject to the constraints imposed by the available data. Specifically, I decompose retail prices into the following components: those due to (1) manufacturer actions including wholesale prices and side payments, (2) retail competition, (3) the retailer's objectives regarding the store brand, and (4) retailer markup from the nature of demand functions facing the chain. I carry out the empirical analysis on the analgesic product category. Consistent with the recent literature on empirical channels research (see Sudhir 2001) and other related studies such as Besanko, Gupta, and Jain's (1998; hereafter BGJ), I use the logit demand model with an outside good as the empirical demand specification. Furthermore, similar to Berry, Levinsohn, and Pakes (1995; hereafter BLP) and Nevo (2001), I estimate a random coefficients version of the logit model. Such a demand system is more flexible than the standard logit model in that it allows for a more general pattern of cross-price elasticities. At the same time, it retains the advantage of parsimony over linear, log–log, and other demand systems.

The results indicate the following: (1) The retail price for certain national brands reflects side payments made by manufacturers to the retailer; (2) to build market share, the retailer prices the store brand below category profit-maximizing levels; and (3) store traffic and competitive retail considerations seem to affect the prices of some of the national brands in the product category analyzed. The implications of these results for manufacturers, retailers, and researchers are discussed in the concluding section of the article.

The main contributions of this study are as follows: (1) It discusses the multiple objectives a retailer must consider while setting retail prices for the different brands in a product category. (2) It provides a decomposition of the retail price of a brand into several components—wholesale price, markup, side payment effects, store traffic effects, and so forth. In this way, the relative importance of each driver of retail price can be evaluated in an empirical context. (3) On the demand side, it applies some of the recent developments in the empirical industrial organization literature to estimate a random coefficients logit model with aggregate data. (4) It provides an empirical analysis of a specific product category for a retailer and estimates the effects of the different drivers of retail prices.

The rest of this article is organized as follows: In the next section, I develop the model formulation that takes into account the different factors driving retailer pricing behavior. I then construct the empirical model that facilitates estimation of the demand parameters as well as the unique parameters in the pricing equations. The following section provides empirical results from the analgesic product category. The final section provides a summary and implications.

MODEL

Discrete choice models have recently been used to characterize the demand for brands in a category (e.g., Berry 1994; BGJ). In contrast with linear and log–log models that have traditionally been used to model retail chain data, discrete choice models rarely result in incorrect signs for the own- and cross-price sensitivity coefficients in the demand functions. This makes them more appealing, especially in situations in which the primary purpose is an understanding of pricing and its effects. A major drawback of the discrete choice model BGJ use, however, is the restrictions it places on the pattern of cross-elasticities across brands. Specifically, the model constrains the elasticities of Brands A and B with respect to the price of Brand C to be the same. In the context of individual-level data, this issue can be addressed by allowing households to differ in their preferences and price sensitivities across brands. For early examples of such analyses, see Hausman and Wise (1978) and Beggs, Cardell, and Hausman (1981), and for a marketing application, see Kamakura and Russell (1989). Aggregate shares will then be free from the restriction. Recent research in the economics literature (BLP; Nevo 2001) has applied such random coefficients versions of the logit discrete choice model that allow for a flexible pattern of cross-elasticities among brands with aggregate- as opposed to individual-level data. Following, I describe the random coefficients model I use to characterize the demand for brands in the product categories analyzed. I start with the model at the household level and then demonstrate how aggregate shares are obtained by aggregating household-level shares over the distribution of heterogeneity.

Specifically, the probability of household i purchasing brand j in week t is given by

$$(1)\quad P_{ijt} = \exp(\alpha_{ij} + \beta_i p_{jt} + \gamma d_{jt} + \phi p_{jt} d_{jt} + \lambda SD + \mu_{jt}) \Big/ 1 + \sum_{k=1}^{K} \exp(\alpha_{ik} + \beta_i p_{kt} + \gamma d_{kt} + \phi p_{kt} d_{kt} + \lambda SD + \mu_{kt}),$$

where the category consists of K brands, j = 1, 2, 3, …, K; the first K – 1 are national brands; and the Kth brand is the store brand.

P_{ijt} = probability that consumer i purchases brand j in week t,
α_{ij} = consumer i's intrinsic preference for brand j,
β_i = price sensitivity parameter for consumer i,
p_{jt} = price of brand j in week t,
γ = deal (promotion) parameter,
d_{jt} = deal (promotion) variable for brand j in week t,
ϕ = interaction effect between price and deal,
λ = effect of seasonal dummy,
SD = seasonal dummy for summer (preliminary analysis indicated no significant differences across the other seasons), and
μ_{jt} = unobserved term for brand j in week t.

The unobserved term μ_{jt} captures the effects of variables other than prices and deals that are not included in the model and that could drive the probability of a consumer choosing brand j. These could be variables such as shelf location, amount of shelf space, and other demand drivers at the chain or store that vary over time and are correlated with price (e.g., a higher-priced brand receives a more prominent shelf facing). The quantity 1 in the denominator of Equation 1 allows for the household not to make a purchase in the product category and represents the outside option. This allows total category demand to increase or decrease on the basis of the marketing activities of the brands included in the category. Households differ along their preferences as well as price sensitivities. Heterogeneity in intrinsic preferences (α_{ij}) and price sensitivities (β_i) is accounted for as follows:

$$(2)\quad \alpha_{ij} = \alpha_j + \varepsilon_{ij}, \text{ where } \varepsilon_{ij} \sim N(0, \Sigma);$$

$$\beta_i = \beta + \varepsilon_{i\beta}, \text{ where } \varepsilon_{i\beta} \sim N(0, \sigma_\beta^2).$$

In other words, α_j is the mean intrinsic preference level for brand j across households, and β is the mean value of the price sensitivity parameter. The element Σ denotes the covariance matrix of preferences across brands, and the σ_β parameter denotes the standard deviation of the price sensitivity distribution. In addition, it is assumed that the preference parameters are not correlated with the price parameter. In the estimation, restrictions are imposed on the Σ matrix to aid model parsimony while allowing brand preferences to be correlated. No distributional assumptions are made regarding the unobserved term μ_{jt} in Equation 1, except that it has a mean of zero. If brand preferences can be characterized by their constituent attributes, then correlated preferences can also be obtained across brands under the assumption that consumers are heterogeneous in their preferences for these underlying attributes.

Taken together, Equations 1 and 2 yield the random coefficients logit brand-choice model at the household level (with the exception of the error term μ_{jt}). However, data are observed only at the aggregate level. In other words, S_{jt}—shares of brand j in week t, not household-level choices—are observed. Furthermore, p_{jt} and μ_{jt} could be correlated, which would lead to the endogeneity problem. Addressing this latter problem requires instruments for the prices, p_{jt}. I discuss possible instruments in the next section. Estimation of the parameters of the model described in Equation 1, $\Theta = \{\alpha_j, \beta, \gamma, \phi, \lambda, \Sigma, \sigma_\beta, j = 1, 2, ..., K\}$, using aggregate shares S_{jt}, prices, and promotional activities is discussed in detail by BLP, Nevo (2001), and others. The basic idea is to recognize that shares are the aggregation of probabilities. Therefore, the shares can be constructed by first drawing from the heterogeneity distribution, computing the "individual" probabilities, and then aggregating these probabilities to obtain shares. For estimation details, see BLP and Nevo (2001). A sketch of the estimation strategy is provided subsequently.

The retailer's problem is to choose the vector of prices in week t, $\mathbf{p}_t = (p_{1t}, p_{2t}, ..., p_{Kt})$ for the K brands in the category. The extant marketing literature (see, e.g., BGJ; Raju, Sethuraman, and Dhar 1995; Zenor 1994) typically assumes that the retailer chooses prices to maximize category-level profits. As is described in the introduction, the retailer may have multiple objectives. These are to maximize (1) category profits and (2) the share of the store brand. One approach to specifying the retailer's optimization function in the presence of multiple objectives is as a weighted sum of the individual objectives (see, e.g., Yu 1989). The weights would then correspond to the relative importance of the objectives to the retailer. Because these relative importance weights are unknown in this study, the proposed methodology should help in the empirical estimation of them. The retailer's objective function can be written as

$$(3)\quad \prod_R = \max_{\mathbf{p}_t} \left\{ \left[\underbrace{\sum_{k=1}^{K} (p_{kt} - c_{kt}) S_{kt} M_t}_{\text{(i) Category Profits}} \right] + \underbrace{\omega_s S_{Kt}}_{\text{(ii) Store brand share}} \right\},$$

where c_{kt} is the price charged by the manufacturer of brand k in week t, Π_R is the objective function for the retailer, and M_t is the potential market size in week t. Note that the assumption of constant costs in Equation 3 is not entirely realistic because of the availability of quantity discounts to the retailer. However, because of the absence of information on the discount schedule, this assumption is necessary. The weight ω_s represents the importance of store brand market share relative to the importance of category profits. This weight is unobserved and must be estimated from the data. Note that because the two objectives have different units of measurement, the weight also adjusts the objectives into common units. The weighted profit function in Equation 3 can be construed as a reduced form to a larger multicategory profit-maximizing problem for the retailer that explicitly accounts for the umbrella branding effect of the store brand. In the presence of such a cross-category effect, the retailer would be expected to lower the price of the store brand to increase that brand's share if purchasing the store brand in one category has a positive influence on purchasing it in other product categories. As is shown subsequently, the construction of the objective function in Equation 3 serves a similar purpose; that is, the retailer lowers the price of the store brand to build its share.

The first-order necessary conditions for the retailer's problem are

$$(4)\qquad \frac{\partial \Pi_R}{\partial p_{jt}} = 0,\ j = 1, 2, ..., K.$$

The first-order necessary conditions for the retailer's profit maximization can be written as

$$(5)\qquad p_{jt} = c_{jt} - \frac{s_{jt}}{s_{jt}^j} - \sum_{\substack{k=1 \\ k\neq j}}^{K}(p_{kt} - c_{kt})\frac{s_{kt}^j}{s_{jt}^j} - \frac{\omega_s}{M_t}\frac{s_{Kt}^j}{s_{jt}^j},$$

$$j = 1, 2, ..., K$$

$$s_{kt}^j = \frac{\partial s_{kt}}{\partial p_{jt}}.$$

In Equations 4 and 5, s_{jt}, j = 1, 2, …, K, denotes the predicted share of brand j in week t obtained from Equations 1 and 2. In other words, the probability expression for consumer i from Equation 1 must be aggregated over the distribution of consumer preferences and price sensitivities given in Equation 2 to obtain the predicted (or unconditional) share. This is accomplished by integrating over the region of the unobserved variables that leads to the choice of brand j. Because convenient closed-form solutions to these integrals are not available, the integral is computed numerically as the sum of several draws from the heterogeneity distributions. Note that because of the presence of heterogeneity, the derivatives in Equations 4 and 5 do not simplify. Solving the system of equations in a two-brand case (say, Brand 1 and Brand K) would yield

$$(6)\qquad p_{1t} - c_{1t} = \frac{s_{Kt}^1 s_{Kt} - s_{1t}s_{Kt}^K}{s_{1t}^1 s_{Kt}^K - s_{Kt}^1 s_{1t}^K}$$

$$p_{Kt} - c_{Kt} = -\left(\frac{\omega_s}{M_t}\right) + \frac{s_{1t}s_{1t}^K - s_{1t}^1 s_{Kt}}{s_{1t}^1 s_{Kt}^K - s_{Kt}^1 s_{1t}^K}.$$

The price-cost margins for the retailer reveal two things: First, as expected, the margins depend on the demand parameters as reflected by s_{jt} and its derivatives. Second, the margins also are a function of the retailer's objectives. Specifically, the larger the weight placed on the share objective of the store brand (ω_s), the lower will be the price of that brand. The extent of this effect on retail prices can be determined when the weight has been estimated. Another point of interest from Equation 6 is that it is easy to verify that the implied price-cost margins for the retailer are not equal across brands as in BGJ's no-heterogeneity case.

Accounting for Side Payments and (Other) Retailer Costs

As noted previously, these payments are over and above the off-invoice discounts and other temporary price reductions offered by manufacturers (which would be reflected in c_{jt} in Equation 5). There are several different approaches to analyzing the effects of side payments. Kim and Staelin (1999) model these payments as driving the retail-level demand functions of brands through merchandising activities. The retailer, however, does not use the entire amount provided by the manufacturer but passes through only a portion of the side payment for merchandising activities to stimulate demand. The remainder of the payment goes directly to increasing the retailer's profits. Using this setup, the equilibrium amount of side payment and pass-through can be determined.

In this case, I do not observe the side payments or the pass-through. But the portion of the side payments not used for merchandising activities could influence the retailer's prices, as in Kim and Staelin's (1999) work. In other words, the retailer could be passing through a portion of the side payments as lower retail prices. Effectively, the observed retail prices will correspond not to the reported manufacturer prices (as these reflect only promotions such as off-invoice discounts) but to some lower level of those prices. Stated differently, the impact of the side payments on retail prices can be modeled as a lowering of the cost to the retailer of the manufacturer's product. Although the amounts by which costs are lowered and their timing are not observed, the average (over time) amounts by which manufacturers' prices are lower because of side payments can be estimated from the available data. The proposed approach accounts for side payments to the extent that the retailer takes them into account while setting retail prices. It does not take into account payments that the retailer does not pass through to consumers, because these payments would represent fixed increments to the retailer's profit function that will drop out of the optimization.

Although side payments lower the retailer's costs, the retailer could incur other, brand-specific expenditures that could increase its costs. Retailer costs related to each of the brands and not accounted for by the data at hand therefore have the opposite effect to the side payments described previously. Given this, the two effects cannot be separated out. However, as is described subsequently, the net effect from the data can be estimated. If the net effect is such that manufacturer prices are lowered, this implies that side payments exceed costs. If the manufacturer prices are raised, then the reverse is true. The approach provided subsequently accounts for any such costs to the extent that the retailer takes them into account while setting retail prices.

Denote by r_k the (unobserved) average per-unit net reduction in the price charged by the manufacturer of brand k to the retailer as reflected by that brand's retail price. Then, the retailer's objective function can be written as

$$(7)\qquad \prod_R = \max_{\mathbf{p}_t}\left(\left\{\sum_{k=1}^{K}[p_{kt} - (c_{kt} - r_k)]S_{kt}M_t\right\} + \omega_s S_{Kt}\right).$$

It is assumed here that there are no side payments or additional costs for the retailer's store brand.

If K is the index of the store brand, then $r_K = 0$. The pricing first-order conditions associated with the preceding profit function can be obtained as

$$(8)\quad p_{jt} = c_{jt} - r_j - \frac{s_{jt}}{s_{jt}^j} - \sum_{\substack{k=1 \\ k\neq j}}^{K}[p_{kt} - (c_{kt} - r_k)]\frac{s_{kt}^j}{s_{jt}^j} - \frac{\omega_s}{M_t}\frac{s_{Kt}^j}{s_{jt}^j},$$

$$j = 1, 2, ..., K.$$

Because of its impact on the retailer's costs, Equation 8 indicates that the side payments will affect the retail prices for the brands in the product category. Again, considering the simple case with two brands, 1 and K, the retailer's markups can be written as

$$(9)\qquad p_{1t} - c_{1t} = -r_l + \frac{s^1_{Kt}s_{Kt} - s_{1t}s^K_{Kt}}{s^1_{1t}s^K_{Kt} - s^1_{Kt}s^K_{1t}}.$$

It is clear that retail prices for the national brands fall when the net effect of side payments and other retailer costs is greater than 0. The empirical analysis shows how the unknown quantity r_k can be estimated. Intuitively, however, these quantities can be identified only if the costs c_{jt} are observed. If those costs are also unobserved, the manufacturer prices cannot be separated out from the side payments in the estimation.

Accounting for Store Traffic Effects

In the previous two cases—accounting for multiple retailer objectives and for side payments—the retailer's category profit-maximizing problem was modified to accommodate the corresponding effects. Another reason for the chain to price below the profit-maximizing levels is if there are store traffic considerations. As noted previously, the chain could react to the competing chain that is promoting in certain categories and drawing customers away from the chain by offering promotions of its own in the following weeks. Ideally, given data from the major competing chain across several categories, attempts could be made to estimate the direct effect of competition across chains. This would be consistent with the extant theoretical literature (Choi 1991; Kim and Staelin 1999). As noted previously, because there is no data on competitor promotions, store traffic in previous weeks is used to proxy for competitor promotions in those weeks. Although this accounts only for the indirect effects of retail competition on retail prices in a product category, it could nevertheless provide some insight into whether pricing in a particular product category is driven by competitive or store traffic considerations. This approach does not address whether the lower retail prices affect store traffic but only whether the retailer responds to a lower level of chain traffic by lowering prices in the product category under consideration.

To account for the effects of store traffic in several previous weeks on retail prices in a particular week, we create a cumulative store traffic variable (CT), an exponentially smoothed version of the store traffic (T) in previous weeks. Specifically, this variable is defined as follows:

$$CT_t = \tau T_{t-1} + (1 - \tau)CT_{t-1},\ 0 \le \tau \le 1.$$

A value of τ close to 1 implies that traffic in the most recent week drives prices in the current week, whereas a value close to 0 indicates that historical store traffic numbers play a larger role in accounting for the effects of store competition on retail prices. The value of τ can be estimated directly or obtained through a search by trying out different values of the smoothing parameter and picking the one that best fits the data (Gupta 1993). In the empirical analysis, I tried both approaches. Now, in the setup, a lower store traffic number implies a higher level of retail competition. To translate traffic measure into a retail competition measure, I set the value of the retail competition variable in week t, $R_t = \ell n(1 \div CT_t)$. In this way, a higher level of cumulative store traffic would imply a lower level of retail competition. I use the log transform, as it resulted in a better fit to the data. Let the vector $\mathbf{P}_t$ denote the solution to the system of Equations 8; then, the effects of store traffic on retail prices are given as follows:

$$(10)\qquad P_{jt} = \theta_j R_t + \mathbf{P}_{jt}.$$

In Equation 10, θ is the brand-specific effect on retail price of brand j. If the retailer is using the price of a brand or a subset of brands in this category to react to higher retail competition levels, it would be expected that $\theta < 0$. In other words, the retailer lowers prices in reaction in lower traffic numbers to draw more consumers into the store.

ESTIMATION ISSUES

The estimation task at hand is to obtain estimates for the various model parameters introduced in the previous section. These are as follows:

1. The set of demand parameters $\Theta_1 = \{\alpha_j, \beta, \gamma, \phi, \lambda, \Sigma, \sigma_\beta, j = 1, 2, ..., K\}$ and
2. Parameters of pricing equations $\Theta_2 = \{r_j, j = 1, 2, \ldots, K - 1; \omega_s, \tau, \theta_j, j = 1, 2, \ldots, K\}$.

Because the pricing equations share the demand parameters with the demand equations, the two sets of parameters are estimated simultaneously by means of the demand functions as well as the retailer pricing equations. This is consistent with recent studies in marketing that, on the basis of the empirical industrial organization literature, recommend such an approach (Cotterill, Putsis, and Dhar 2000).

The estimation strategy closely parallels that laid out by Berry (1994). The errors on the demand side stem from the unobservable term μ_{jt} in Equation 1. Furthermore, as noted previously, the observed wholesale price wp_{jt} does not perfectly reflect the retailer's cost for brand j in that week. Therefore, c_{jt} can be written as $c_{jt} = wp_{jt} + \eta_{jt}$. The term η_{jt} denotes the mean zero error in the observed wholesale prices and becomes the error in the pricing equation. In the simple two-brand case, the pricing equation for Brand 1 can be written as the sum of six components: the cost, side payments if any, markup, store traffic effect, store brand market share weight effect, and error:

$$(11)\qquad p_{1t} = \underbrace{wp_{1t}}_{\text{Cost}} - \underbrace{r_l}_{\substack{\text{Side}\\ \text{payment}}} + \underbrace{\frac{s^1_{Kt}s_{Kt} - s_{1t}s^K_{Kt}}{s^1_{1t}s^K_{Kt} - s^1_{Kt}s^K_{1t}}}_{\text{Markup}} + \underbrace{\theta_1 R_t}_{\text{Traffic effect}} + \underbrace{\eta_{1t}}_{\text{Error}}$$

$$p_{Kt} = \underbrace{wp_{Kt}}_{\text{Cost}} - \underbrace{\left(\frac{\omega_s}{M_t}\right)}_{\substack{\text{Share weight}\\ \text{effect}}} + \underbrace{\frac{s_{1t}s^K_{1t} - s^1_{1t}s_{Kt}}{s^1_{1t}s^K_{Kt} - s^1_{Kt}s^K_{1t}}}_{\text{Markup}} + \underbrace{\theta_K R_t}_{\text{Traffic effect}} + \underbrace{\eta_{Kt}}_{\text{Error}}.$$

Equation 11 implies the following for the retail price of Brand 1 (a national brand). The larger the side payment from the manufacturer to the retailer, the lower is the retail price of Brand 1. Furthermore, if $\theta_i < 0$, this implies that more retail competition (i.e., lower store traffic) in previous weeks triggers a lower price for that brand in subsequent weeks. For the store brand, the larger the weight placed on the store brand's share maximization objective, the lower is the retail price. Equation 11 can also be written in a form similar to the pricing equations (3.6) in BLP.

$$(12)\qquad p_{1t} - wp_{1t} - \frac{s^1_{Kt}s_{Kt} - s_{1t}s^K_{Kt}}{s^1_{1t}s^K_{Kt} - s^1_{Kt}s^K_{1t}} = -r_l + \theta_1 R_t + \eta_{1t}$$

$$p_{Kt} - wp_{Kt} - \frac{s_{1t}s^K_{1t} - s^1_{1t}s_{Kt}}{s^1_{1t}s^K_{Kt} - s^1_{Kt}s^K_{1t}} = -\left(\frac{\omega_s}{M_t}\right) + \theta_K R_t + \eta_{Kt}.$$

The estimation strategy is as follows: Given a set of starting parameters, the set of demand-side errors can be computed from the "contraction mapping" step described in Berry (1994), BLP, and Nevo (2001). The predicted brand shares from the model are computed through simulation. For each week, 1000 draws were made from the heterogeneity distribution for this purpose. Similarly, supply-side errors can be computed from the pricing equations (such as Equation 11). The demand- and supply-side errors are interacted with a set of instruments, which are then fed into the generalized method of moments objective function.

Another issue to be resolved prior to the estimation is the specification of the covariance matrix of brand preferences, Σ. In previous studies, the correlation in brand preferences has come from brands that share a subset of attributes that characterizes them. In this case, given the aggregation of sales to the brand level (the data are described subsequently), the information contained in the attributes pertaining to the Universal Product Codes (UPCs) that constitute the brand cannot be exploited. An alternative approach to allowing for preference correlation is therefore required. Given the five brands in the data, estimating all the parameters corresponding to (the Cholesky decomposition of) Σ would result in the estimation of 15 parameters. To avoid the estimation of such a large number of parameters, the following decomposition for the preferences is used:

$$(13)\quad \alpha_{ij} = \alpha_j + \xi\varepsilon_{ij} + \psi_j e_i;\ \ \varepsilon_{ij} \sim N(0,1),\ \ e_i \sim N(0,1).$$

In the specification in Equation 13, ε_{ij} is the brand-specific component of heterogeneity that has an equal variance (ξ^2) across brands, and e_i is the common component (or factor) of heterogeneity, which has a brand-specific variance (ψ_j^2). Therefore, brand j's preference variance is given by $\xi^2 + \psi_j^2$, and the covariance in preferences between brands j and k is $\psi_j\psi_k$. Such a formulation reduces the total number of estimated parameters from 15 to 6 while retaining some flexibility in the brand preference distribution. Additional flexibility is afforded by assuming two values of ξ—one for all national brands and one for the store brand. In total, 7 parameters are estimated.

DATA

The data are provided by a large chain in the Midwest and have now been made available to the entire academic community. The chain competes in a single large metropolitan area and is one of two large chains in this market. There are approximately 96 stores in the chain, but complete historical data are available only for approximately 80 stores. The chain provided weekly store-level scanner data by UPC, including unit sales, retail prices, profit margin (for the computation of wholesale prices), and a promotion variable. Data are available for 25 food (e.g., soup, juices, tuna, cereal, soda) and nonfood (e.g., analgesics, paper towels, toilet tissue) product categories. Although more than seven years of weekly data are available, starting from 1989, attention was restricted to the first four years.

The product category used in the empirical analysis is analgesics. Data are aggregated to the brand and chain level, and store shares are used as weights. The top five brands are included in the analysis. These are Tylenol, Advil, Bayer, Motrin, and the store brand, which is aspirin, just another version of Bayer. Data available for the estimation of the model parameters consist of the sales of the brands; the prices, p_{jt}; the promotional variables, X_{jt}; the manufacturer prices, wp_{jt}; and the chain traffic variable, T_t. In addition to these variables, a dummy variable was used as an independent demand shifter to facilitate identification (a summer-season dummy). The importance of including such shifters is explained by Kadiyali, Vilcassim, and Chintagunta (1999). The data analyzed cover a period of 196 weeks.

The initial step is to convert the sales data into shares, S_{0t}, S_{jt}, j = 1, 2, …, K. For this, the sales of the outside good must be constructed. This was done in two ways and was checked for sensitivity both across and within each method. The first approach assumes that some fraction of households visiting the chain in each week may purchase analgesics. It is assumed that each household consumes four 100-tablet boxes of analgesic a year (approximately one pill a day), and the sensitivity of results to this assumption (2 to 6 boxes) is tested. Under this assumption, the store traffic is converted into a potential consumption number in each week, M_t. The outside good is simply the weekly potential consumption less the total amount of analgesics sold in that week. When this size of outside good is obtained, the share calculation is straightforward. Because store traffic enters into the computation of shares as well as the pricing equation (albeit in lagged form), another approach to computing shares is also explored. The second approach is based on the population in the market area served by the stores in the chain and the conversion of this into potential consumption numbers. In this case, the weekly potential is time invariant. The nature of results obtained from the two approaches is similar.

Instruments

As noted previously, the potential correlation between the demand-side errors (i.e., the unobservable terms) and retail prices requires instrumenting for retail prices. In the estimation, the manufacturer prices (wp_{jt}) as well as interactions among the various wholesale prices ($wp_{jt} \times wp_{kt}$) were used as instruments for retail prices. Instrumental variables are required to satisfy two main conditions: First, they should be correlated with the endogenous variables under consideration. Second, they must be uncorrelated with the error term. In this case, it must be that though manufacturer prices (wp_{jt}) are correlated with retail prices (p_{jt}), they are less likely to be correlated with the unobserved in-store factors such as shelf locations and shelf-space allocations (the μ_{jt} term in Equation 1). The first condition is relatively straightforward to verify. The following section on the empirical analysis presents results from the regression of the retail prices on the instruments and the other exogenous variables included in the analysis.

The second condition is more difficult to verify, because the errors are unobserved. Here, I present arguments on when I believe that manufacturer prices make good instruments and when they do not. It could be argued that when manufacturers themselves set prices, these prices can be written as the sum of two terms—marginal costs and a markup term. The markup is related to factors that drive demand in that market. Because manufacturers are required to set (local) market level prices rather than prices at the chain level, it is expected that this markup term would depend less on chain-specific factors such as shelf-space allocations and shelf locations of brands. Under these circumstances, the correlation between manufacturer prices and the unobserved errors in the chain-level demand function can be expected to be small. However, if manufacturers take into consideration the specific demand drivers in each retail chain while setting their prices, the choice of instruments would be problematic. Other circumstances in which manufacturer prices will not make good instruments would be when the demand errors (μ_{jt}) reflect manufacturer-level decision variables such as television advertising.

The preceding discussion pertains to all situations in which the researcher has access to wholesale price data. Specific to the situation here is the manner in which the wholesale price series are constructed by the chain from which the data are obtained. The reported wholesale price in week t is not the replacement cost in week t but the average cost of inventory held by the chain. This implies that the reported wholesale price depends on current and lagged replacement costs and lagged sales. This is problematic if there is serial correlation in the unobserved term μ_{jt}, because it would imply a correlation between μ_{jt} and the wholesale price at time t, thereby invalidating these wholesale prices as instruments. A possible mitigating factor would be the rapid turnover of inventory in the store, which would minimize the effects of previous-period replacement costs. This is, however, not very likely for the analgesics product category considered here. As described by Hamilton (1994), the weighting matrix in generalized method of moments can account for serial correlation in the errors. The estimation was carried out under the assumptions of no serial correlation and first-order autocorrelation. The results obtained under the two scenarios did not differ significantly from each other. Although this provided some assurance that it may be reasonable to use the reported wholesale prices as instruments, future researchers using these data should explore product categories with higher inventory turns, such as perishables.

Another way to verify whether endogeneity is indeed an issue in a given empirical context would be to compare the results obtained through estimation of the demand function using a method such as nonlinear least squares that does not instrument for prices with those obtained with instrumenting. The results indicate that the price coefficient would be biased toward zero if endogeneity is not accounted for (the price coefficient from the proposed model is –.64 with a standard error of .02; from the proposed model without the retailer pricing equations, it is –.65 with a standard error of .14; and from the model that does not account for endogeneity, it is –.47 with a standard error of .01). (Interested readers can obtain these results from the author.)

I also tried other instruments such as the price indices of input into the manufacture of the products considered. However, these did not work well (see the discussion in the "Results" section). A possible reason is that these instruments do not vary across brands and consequently cannot capture that aspect of the variation in the data. Finally, Hausman, Leonard, and Zona (1994) and Nevo (2001) suggest using prices from other markets as instruments. The advantages and disadvantages of such instruments have been discussed in detail by Nevo (2001). However, such data are unavailable. On the supply side, I use the additional information contained in the store traffic variable and its lags in estimation.

One last point about endogeneity. It has been assumed throughout that though prices and the unobserved attributes can be correlated, the promotion variables (d_{jt}) are uncorrelated with the unobservables. To determine whether promotions are also correlated with the unobserved error term, the results obtained for the promotion parameter when prices were not instrumented for were compared with those obtained when wholesale prices were used as instruments for the promotion variable. If promotions are indeed endogenous, the estimated parameter is likely to change when prices are instrumented for. When prices are not instrumented for, the estimated promotion parameter is .30 (standard error .16). Under the proposed model specification, the promotion parameter is .27 (standard error .14). And under the proposed specification without the retailer pricing equations, the estimate is .24 (standard error .60). Therefore, the promotion parameter seems relatively unaffected across the various models estimated.

EMPIRICAL RESULTS

The descriptive statistics for the data sets are in Table 2. The only nonprice variable included is special displays. This variable is referred to as the promotion variable and is operationalized as the fraction of UPCs for a brand with in-store displays. In addition to the variables shown in Table 2, there is also information on the store traffic count in each week.

Table 2 reveals the following: (1) The retail price is lowest for the store brand, (2) the manufacturer price is also lowest for the store brand, (3) the store brand has the highest sales level in the analgesic category, (4) the data reveal a large difference in the retailer's margins between the store brand and the national brands—58% for the store brand compared with 11%–18% for the national brands, and (5) all brands are promoted about the same in this particular category.

Before fitting the empirical model described in the previous section to the data, I tried to identify whether the chain was following any simple pricing rules. The model presented by BGJ suggests that retailers charge an identical markup (i.e., retail price – wholesale price) across all brands in the category. Table 2 indicates that, on average, this is not

Table 2
DESCRIPTIVE STATISTICS OF THE DATA

	Tylenol	*Advil*	*Bayer*	*Motrin*	*Store*
Sales (units)	1424	369	498	489	2077
Retail price ($/100 tablets)	6.16	7.41	4.59	5.95	3.55
Manufacturer price ($/100 tablets)	5.32	6.07	4.06	5.18	1.50
Retailer margin	.84	1.34	.53	.77	2.05
Retailer margin (% of retail price)	14	18	11	13	58
Promotion[a]	.05	.07	.12	.12	.08

[a]The numbers corresponding to the promotion variable represent the average proportion of the product sold on promotion (special display) each week.

Table 3
REGRESSION OF PRICE ON MATRIX OF INSTRUMENTS[a]

	Parameter	*Standard Error*
Tylenol wp[b]	.639	.065
Advil wp	–.501	.084
Bayer wp	1.446	.094
Motrin wp	.605	.032
Store brand wp	1.551	.102
Own brand wp × Rival 1 wp[c]	.014	.004
Own brand wp × Rival 2 wp	–.014	.003
Own brand wp × Rival 3 wp	–.007	.003
Own brand wp × Rival 4 wp	.030	.007
Current period price index	.008	.006
One period lagged price index	–.001	.007
Two periods lagged price index	–.004	.007
Three periods lagged price index	–.003	.005
R-squared	.96	
F-statistic	1184	

[a]The regression includes brand-specific intercepts and other exogenous variables considered in the analysis.
[b]wp = wholesale price (wp_{jt}).
[c]Brand-specific effects did not improve fit for these variables.

the case. In addition, if the retailer indeed follows such a pricing rule, the computed markups should be highly (positively) correlated across brands within a category.

Another pricing rule commonly attributed to retailers is the equal margin rule (see Blattberg and Neslin 1990). The idea is that the retailer expects to make a margin ([retail price – wholesale price]/retail price) of, say, 30% for a particular category. Therefore, retail prices for brands within that category are chosen such that the value of (retail price – manufacturer price)/retail price = .30 for all brands. If this is the case, the computed margins should be highly (positively) correlated across brands. Table 2 indicates that, on average, neither of these rules is consistent with the data. Furthermore, the markups and margins described previously were correlated. These correlations clearly indicated that neither the equal markup nor the equal margin rule is consistent with these data.

The results are discussed in the following order: I begin by discussing the estimates obtained by regressing the retail prices on the instruments and other exogenous variables. The fit of this regression provides some insights as to whether the chosen instruments have power. I then present the demand function parameters, followed by a discussion of the parameters unique to the pricing equations. Finally, I attempt to explain the relative importance of various factors that drive observed retail prices.

Table 3 provides the results from the regression of the endogenous variable price on manufacturer wholesale prices, the interaction of the wholesale prices with one another, and the other exogenous variables in the model. Some explanation of this regression is in order. The dependent variable in the regression is price. The price vector is obtained by stacking the prices of all brands over the 196 weeks of the data into a single-column vector in which all the prices of Tylenol come first, followed by all the prices of Advil, and so forth. The independent variables are the brand intercepts, the instruments, and other exogenous variables. The instruments used are the wholesale prices of the five brands, the interactions between the wholesale price of a brand and those of its rivals, and current and lagged price indices. Interacting the wholesale prices with the brand intercepts improved fit. Therefore, brand-specific wholesale price effects are reported in Table 3. These are valid instruments, as they are functions of other instruments. (Formally, if $E[\boldsymbol{\mu}|\mathbf{Z}] = 0$, where $\boldsymbol{\mu}$ is the vector of unobserved attribute terms in Equation 1 and $\mathbf{Z}$ is the vector of instrumental variables, then $E[\boldsymbol{\mu}|f(\mathbf{Z})] = 0$. Therefore, $f[\mathbf{Z}]$ are also valid instruments.) The finding that emerges from these parameter values (the first five in Table 3), is that though prices appear to be positively correlated with wholesale prices for four of five brands, they are not so in the case of Advil. According to Table 2, Advil is the smallest national brand, is the most expensive, and provides the highest margins to the retailer. Researchers have noted that the pass-through for small brands tends to be quite low given their low relative power (see Blattberg and Neslin 1990). It is probable that the retailer, given the small size of the brand, could be raising prices at times of manufacturer promotion to maximize profits from the small base of loyal Advil users. (As is shown subsequently, Advil has the second-highest intrinsic brand preference level among the products considered.) The other set of instruments used is the interactions among the wholesale prices. Again, these are valid instruments. Table 3 indicates that the price index variables do not play a significant role in explaining the price variations. A possible reason for this finding is that the data are provided on a weekly basis whereas the indices vary only by month. The results in Table 3 indicate a high value of R^2 (and adjusted R^2). A formal F-test demonstrates the significance of the overall regression. This provides some assurance that the chosen instruments have some power. Similar to previous studies, however, the hypothesis of all sample moments being equal to zero is rejected on the basis of Hansen's (1982) χ^2 test (for a discussion on possible reasons for this finding, see Nevo 2001).

Table 4 presents the parameter estimates and their standard errors for the various demand parameters obtained for the analgesics data. Note that though these parameters are from the demand functions, they also appear in the pricing equations. The estimates obtained are provided using only the demand function without the pricing equations in the estimation ("Only Demand" column) and those obtained from the full model ("Proposed Model" column). Note that the only-demand model is similar to Nevo's (2001) specification but without the product attributes and market demographic variables that are included in Nevo's analysis.

Prima facie, the results in Table 4 indicate that the estimates obtained from the two model specifications are comparable. In particular, the effects for price, promotion, and the mean intrinsic preferences are similar across both specifications. However, there are a few differences. In particular, the mean intrinsic preference for the Motrin brand is smaller under the only-demand specification. Furthermore, compared with the proposed model formulation, that specification indicates a greater amount of heterogeneity in preferences for the national brands. To ensure that there is no contamination of estimated effects due to misspecification in the pricing equations under the proposed specification, I compared the price elasticities from the two models. These elasticities indicated only minor differences across the two model specifications. This gave some assurance as to the reasonableness of the proposed specification.

Table 4
DEMAND PARAMETER ESTIMATES AND STANDARD ERRORS

	Only Demand	Proposed Model
Variable	*Parameter Estimate (Standard Error)*	*Parameter Estimate (Standard Error)*
Price (mean)	–.65	–.64
	(.14)	(.02)
Price (S.D.)	.06	.18
	(.03)	(.01)
Promotion	.23	.27
	(.60)	(.14)
Tylenol (mean)	–1.40	–1.38
	(.40)	(.07)
Advil (mean)	–2.02	–2.15
	(.34)	(.06)
Bayer (mean)	–3.80	–3.39
	(.60)	(.12)
Motrin (mean)	–5.14	–2.88
	(.84)	(.11)
Store (mean)	–2.08	–2.57
	(.66)	(.12)
Tylenol (S.D)	1.22	.37
	(.41)	(.13)
Advil (S.D)	1.25	.30
	(.36)	(.13)
Bayer (S.D)	1.49	.83
	(.57)	(.16)
Motrin (S.D)	2.69	.93
	(.76)	(.13)
Store (S.D)	.62	.97
	(.89)	(.25)

Notes: S.D. = standard deviation.

For the specific estimates in Table 4, first note the ordering of the mean intrinsic preferences of brands. Table 4, for the proposed-model specification, indicates that Tylenol has the highest mean preference, followed by Advil, the store brand, Motrin, and Bayer. Significantly, this ordering is in contrast with the ordering of brand shares (from Table 2), which reveals that the store brand has the highest share, followed by Tylenol, Bayer, Motrin, and Advil. This finding implies that it is important to control for the effects of marketing activities before making statements about the relative preferences for brands in a category.

Table 4 also shows that the variance associated with brand preferences—that is, the amount of heterogeneity in consumer preferences for the different brands—differs substantially among the various brands. The store brand appears to have the highest amount of heterogeneity associated with its preferences. This is followed by Motrin, Bayer, Tylenol, and Advil. The low variances for the latter two national brands compared with the store brand reflect time in market and advertising efforts by the manufacturers of these brands (Keller 1998).

In contrast with the relatively high variance in brand preferences, Table 4 shows that consumers do not appear to be very heterogeneous in their price sensitivities. The variance from the proposed model is .0324 (.18 × .18), though the underlying parameter is significantly different from zero. The low heterogeneity in price sensitivities could be due to the nature of the product category, that is, a pharmaceutical product. Although the price sensitivity parameter also appears small (–.64), this number is difficult to interpret without being converted into elasticities. Accordingly, Table 5 provides the matrix of average price elasticities for the brands in this product category.

Advil has the highest own-price elasticity, followed by Tylenol, Motrin, Bayer, and the store brand. Table 5 indicates that the ranking of the magnitudes of own-price elasticities (from smallest to largest) is similar to the ranking of the average prices in Table 2. This implies that though preference correlations across brands are allowed for, the one-factor structure for the random effects (Equation 13) may not be rich enough to allow a general pattern of correlation. Although this study was constrained by the data, further research can address this issue. The cross-elasticities, however, indicate some deviation from independence from irrelevant alternatives. For example, the cross-elasticities of Tylenol prices on rival brands range from .037 (standard error .029) to .050 (standard error .031), a ratio of 1.35:1, and for Advil and Motrin, this range is 1.45:1. However, the ranges for Bayer and the store brand are closer to 1. Again, this calls for a richer heterogeneity specification.

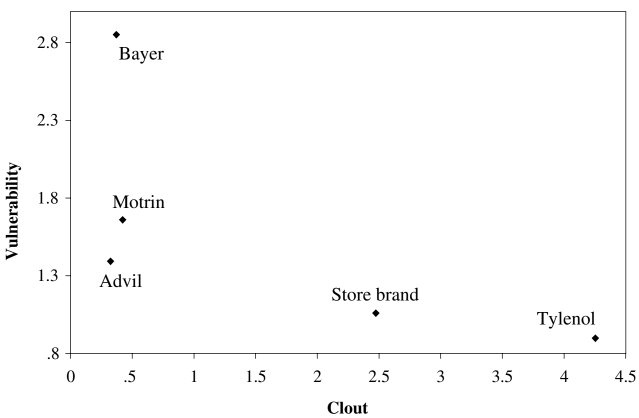
The cross-elasticities in Table 5 indicate that the brand whose price has the biggest impact on competitor shares is Tylenol. This is followed by the store brand, Advil and Motrin, and, finally, Bayer. We also find that the cross-price elasticities are small. This is because each brand's share is small compared with the share of the outside good. To obtain a better sense of the cross-elasticities, I computed the "conditional" cross-elasticities, that is, those obtained by eliminating the outside good. I then summarize these cross-elasticities by means of the clout and vulnerability measures described by Kamakura and Russell (1989). Doing so, I obtain the configuration in Figure 1.

The map in Figure 1 indicates that Tylenol has the highest clout, followed by the store brand and then by Motrin, Bayer, and Advil. In terms of vulnerability, Tylenol and the

Table 5
PRICE ELASTICITIES FROM PROPOSED MODEL

Price/Share	*Tylenol*	*Advil*	*Bayer*	*Motrin*	*Store*
Tylenol	–2.685	.050	.041	.045	.037
	(.411)	(.031)	(.022)	(.025)	(.029)
Advil	.016	–2.986	.013	.015	.011
	(.011)	(.529)	(.009)	(.009)	(.010)
Bayer	.010	.011	–2.254	.011	.009
	(.006)	(.006)	(.435)	(.005)	(.006)
Motrin	.015	.016	.014	–2.660	.011
	(.008)	(.007)	(.008)	(.444)	(.006)
Store	.030	.031	.029	.031	–1.808
	(.017)	(.015)	(.015)	(.015)	(.517)

Figure 1
CLOUT–VULNERABILITY MAP



store brand are the least vulnerable brands, followed by Advil, Motrin, and Bayer. Given that Bayer is the branded version of aspirin and the store brand is the unbranded version of the same product, Bayer's vulnerability seems plausible, especially given the price differential compared with the store brand.

To conclude the discussion from Table 4, as expected, promotions have a positive and significant effect on demand for the brands. The effects are comparable across the two specifications whose results are presented in Table 4.

The parameters estimated from the pricing equations include the parameters characterizing the side payments from the national brand manufacturers to the retailer, relative weight on store brand market share objective (ω_s), and the parameters capturing the effects of store traffic on prices. Table 6 provides these estimates and standard errors.

The estimates in Table 6 indicate that all four national brand manufacturers—Tylenol, Advil, Motrin, and Bayer—may indeed be making side payments to the retailer, and these exceed any additional costs borne by the retailer that are variable in nature. The payments are largest for Bayer, followed by Motrin, Advil, and Tylenol. In Bayer's case, the estimate translates into a payment of $1.59 (standard error .22) from the manufacturer to the retailer. Why does Bayer need to make such large payments to the retailer? Recall the previous discussion, which was based on the demand parameters, that Bayer has a low level of clout in this market. Furthermore, the retailer's store brand is therapeutically identical to Bayer. This seems to impart considerable power to the retailer over Bayer. The smallest value for Tylenol ($1.21, standard error .20) is consistent with its high clout and low vulnerability.

Another factor that is incorporated into the analysis is the multiple objective nature of the retailer's pricing problem. The proposed formulation allows for the retailer to assign some nonzero weight to the share of the store brand in the objective function. The rationale for this is described in the introduction. The estimates in Table 6 indicate that the retailer does assign a significant weight (3.65, standard error .23) to the share of the store brand. From the discussion of the pricing equations, recall that a larger weight implies a lower store brand price than is category profit maximizing.

Table 6
PARAMETERS OF THE PRICING EQUATIONS

Variable	*Parameter Estimate (Standard Error)*
Net side payment Tylenol	1.21 (.20)
Net side payment Advil	1.25 (.23)
Net side payment Bayer	1.59 (.22)
Net side payment Motrin	1.56 (.23)
Weight on store brand share	3.65 (.23)
Store traffic effect Tylenol[a]	–.51 (.26)
Store traffic effect Advil	–.02 (.28)
Store traffic effect Bayer	.01 (.27)
Store traffic effect Motrin	–.01 (.28)
Store traffic effect store brand	.37 (.23)
Store carryover effect	.60[b]

[a]The store traffic variable was scaled down by multiplying it by the factor 1e – 5. The effect reported corresponds to the scaled variable.
[b]This was fixed in the estimation.

Thus, it appears that the retailer is willing to give up some profits in pursuing a higher share for the store brand. I return to the relative impact of this weight, in relation to the side payment and store traffic effects, subsequently in the section.

The final set of parameters in Table 6 involves whether store traffic or retail competition in previous weeks drives retailer pricing in the analgesics category. Note from Equation 11 that the model allows for several lags to affect retail prices. The smoothing parameter (τ) was obtained through a search procedure over the range [0, 1]. The search yielded a value .60 that corresponded to the lowest value of the estimation objective function. The results presented correspond to the search value of .60. The value .60 indicates that the relative importance of the most recent week's store traffic is slightly larger than the importance of all preceding weeks' traffic. However, both seem to play a role in determining retail prices. Table 6 reports five parameters for store traffic effects, one for each brand in the analysis.

The estimates in Table 6 reveal that previous periods' traffic seems to influence pricing behavior in the case of Tylenol and the store brand, albeit quite differently. In particular, prices seem to be adjusted downward with retail competition for Tylenol. In other words, the results seem to indicate that a lower customer count or greater retail competition in a given week is followed by lower prices for this national brand in subsequent weeks. The store brand, however, indicates positive effects. Although I do not have a good explanation for this finding, note that the results for the store brand are consistent with those of Dhar and Hoch (1997), who find that retailers primarily use national brands but not the store brand to drive store traffic.

Decomposing Retail Prices

The results thus far indicate that side payments and store traffic effects appear to play a role in retail prices for some

Table 7
DECOMPOSITION OF (AVERAGE) RETAIL PRICES

Brand	*Wholesale Prices*	*Markup*	*Side Payments*	*Store Brand Objectives*	*Store Traffic Effect*	*Retail Prices*
Tylenol	$5.32	$2.37	$1.21	—	–$.32	$6.16
		(.74)	(.20)		(.13)	
Advil	$6.07	$2.60	$1.25	—	–$.01	$7.41
		(.88)	(.23)		(.15)	
Bayer	$4.06	$2.12	$1.59	—	$.01	$4.59
		(.85)	(.22)		(.15)	
Motrin	$5.18	$2.34	$1.56	—	–$.01	$5.95
		(.85)	(.23)		(.16)	
Store brand	$1.50	$2.01		$.19	$.23	$3.55
		(.91)	—	(.09)	(.11)	

Notes: Retail price = wholesale price + markup – side payments – store brand objectives + store traffic effect. Errors in markup computation account for any differences from the actual retail prices.

of the national brands. Furthermore, the retailer considers the store brand to be of strategic importance and is trying to maximize that brand's share in addition to maximizing analgesic category profits. The question then is, How can the relative effects of these factors on the retail prices of the brands be compared? To answer this question, Table 7 presents the breakdown of each brand's (average) retail prices into the following: (1) manufacturers' reported wholesale prices, (2) markup based on the demand function estimates (this corresponds to the markup term in Equation 11), (3) side payments, (4) retailer's store brand objectives, and (5) store traffic (i.e., retail competition) effect. In this way, the key drivers of retail prices can be identified for each of the brands in the category.

On the basis of the decomposition of retail prices as in Equation 11, the retailer, acting as a multiproduct monopolist, should be making a markup of $2.37 (standard error .74) on the Tylenol brand in the absence of any side payments. This would result in the retail price of Tylenol being $7.69. The actual retail price of Tylenol is only $6.16, $1.53 lower. The primary reason for this is that side payments lower wholesale prices by $1.21 (standard error .20), and store traffic effects lower markups by $.32 (standard error .13). For the store brand, the objective to increase market share lowers that brand's prices by $.19 (standard error .09). This is offset by the store traffic effects ($.23, standard error .11). Thus, the computed markup for the store brand using only the demand parameters appears to reflect the actual markup enjoyed by the retailer for that brand. The increase of $.23 due to retail competition is harder to explain, because the retailer appears to be raising store brand prices as a consequence of retail competition. One possibility is that the retail chain is a "monopolist" when it comes to its own store brand and can consequently charge a higher price. The key takeaway from the retail price decomposition is that if the retailer pricing equation (Equation 11) did not reflect the various aspects such as markups, side payments, retailer objectives, and retail competition, it would be difficult to reconcile the elasticity estimates with the observed retail markups. As the proposed model indicates (and this was also verified by means of the elasticities from the only-demand model), the estimated elasticities are too small to explain the markups. However, allowing for these other factors helps reconcile the elasticity estimates with the observed markups.

In summary, the results from the analysis of the analgesic category are as follows: (1) The chain seems to be taking side payments from the national brand manufacturers into account when setting retail prices, (2) the retailer is pricing the store brand below category profit-maximizing levels because it is attempting to maximize the share of the store brand in addition to maximizing category profits, and (3) store traffic and retail competition considerations affect the prices of some of the brands in this product category.

CONCLUSIONS

In studying the pricing behavior of retailers, researchers typically assume that chains maximize profits across all brands in a focal product category. Recently, the literature in marketing has extended this basic framework to account for other factors that drive retailer behavior—building store traffic, promoting sales of store brands, and so forth. In this article, I have attempted to study empirically the extent to which some of these factors affect retail prices. I do so in the context of a specific product category at a single retail grocery chain. The data available are the weekly chain traffic, unit sales, retail prices, manufacturer prices to the retailer (e.g., net of quantity discounts, temporary price reductions), and the extent of promotions in the category for that chain. By specifying a demand function at the brand-chain level for each brand in the product category, I obtain retail price levels assuming that the retailer has multiple objectives—maximizing category profits as well as the share of the store brand. The pricing equations obtained can be decomposed into the effects of costs, markups, side payments, store traffic effects, and so forth.

The next step was taking the model to the data. This was done for the analgesic product category. It was found that the magnitudes of the side payments exceed additional costs that the retailer might bear in selling these products for all four national brands. In addition, retail prices are sensitive to side payments and to store traffic, and these effects were quantified by their net effects on retail prices. The retailer also seems to be pricing the store brand strategically (compared with the national brands) because of its objective to maximize store brand share. This results in a decrease in the retail price of the store brand.

There are several caveats to the analysis. The entire analysis is carried out conditional on manufacturer prices to the retailer. In other words, it is assumed that the retailer sets prices after observing manufacturer prices. Recent empirical studies have attempted to incorporate the strategic behavior of both manufacturers and retailers in their analysis of channel interactions (see, e.g., Kadiyali, Chintagunta, and Vilcassim 2000; Sudhir 2001). However, given the present objective of understanding retailer behavior, it becomes difficult, if not impossible, to also recover the nature of manufacturer–retailer interactions. It is also assumed that the marketing instrument of interest is price. Although the retailer makes decisions on promotions to be offered, there is no data on costs associated with these promotions. This is a limitation of the analysis. Another limitation of the specification is the manner in which retail competition is accounted for. The operationalization is based on store traffic serving as a proxy for retail competition. As noted previously, a more direct measure of competition is warranted. Furthermore, a specific lag structure is imposed on the store traffic when it is translated into a measure of competition. In reality, retailers, in a given week, may respond to competitor prices only two weeks ago—the lag structure does not allow for this. Theoretically, the model is not restricted to the chosen specification for the lag structure. However, including additional parameters to allow for a more flexible store traffic effect places a greater burden on the data. An alternative explanation for the side payments finding could be measurement error in the reported wholesale prices (i.e., retailer costs). However, the data from the Cannondale survey suggest the existence of such payments in the marketplace.

Therefore, there are multiple directions for further research. Although the effects of side payments and strategic behavior with respect to the store brand were incorporated into the profit-maximizing behavior of the retailer, this was not the case for the store traffic effects. A more complete characterization of the model that takes into account the drivers of store traffic is required. A multicategory model may be better able to capture such a phenomenon. To implement such an approach, however, researchers will need to impose restrictions on the interactions among product categories, as not doing so will result in a large number of parameters to be estimated. This is a nontrivial task. The implications of the model and results for manufacturers, retailers, and marketing researchers are now discussed.

Implications for Manufacturers

From the perspective of the manufacturer of a national brand, the following implications are relevant: First, the demand-side analysis provides implications for interbrand competition among customers of this retail chain. Examining the cross-price elasticities sheds some light on this issue. These estimates are obtained from a parsimonious demand specification, which is flexible but does not result in incorrect signs for the elasticity estimates. In addition, the analysis of clout and vulnerability indicates which brand needs to be most concerned about price competition in this market (in the empirical application, the brand is Bayer). Another implication is based on the covariance matrix of brand preferences. Although these estimates were not discussed in the article, the elements of this matrix aid in the understanding of how preferences are correlated across brands for consumers in this retail chain for the analgesics product category. Therefore, implications similar to other analyses of interbrand competition can be obtained through an examination of the demand estimates obtained from the study (see, e.g., Kamakura and Russell 1989).

Second, manufacturers can also gain a better understanding of retailer pricing and pass-through decisions from the supply side of the analysis. Of particular interest is the extent of pass-through of promotional moneys and side payments. Just observing the retail prices of a chain will not give manufacturers a clear understanding of how promotional moneys are translated into retail prices because of the confounding effects of retail competition. Furthermore, because some of these are lump sum payments, it is even more difficult to understand what components of these fixed payments are translated into lower retail prices. Using the results from this analysis, manufacturers will be better able to understand these effects. For example, Table 6 shows that retail prices of Tylenol reflect the smallest side payments from that brand's manufacturer. If the company did make payments to the retailer, it would be of interest to know whether the manufacturer is receiving the full benefits in terms of retail prices. In doing so, it is important to keep in mind that the retailer could be carrying out other activities to promote the sales of Tylenol that also need to be accounted for by the manufacturer.

Implications for Retailers

The analysis provides some useful insights for retailers as well. On the demand side, there are implications for the retailer's store brand. Specifically, this brand has a relatively high mean intrinsic preference level (Table 4). The retailer therefore can take advantage of the positive equity built up by this brand among its consumers. Specifically, if cross-category or umbrella branding effects exist, the retailer may be able to promote the sales of a store brand in a related category (e.g., antacids) by copromoting that product with the store brand analgesic. One potential caveat would be the high variance in preferences for this brand. The price elasticity matrix (Table 5) also is useful for the retailer to better understand price competition in the market. On the supply side, it is clear that the retailer is under competitive pressure to lower the prices of the flagship national brand—Tylenol. Loyalty programs that could insulate the chain from retail competition may give it some leeway in strategic pricing of analgesics.

Implications for Marketing Researchers

For marketing researchers, this article offers a methodology that has both demand- and supply-side implications. On the demand side, it provides a flexible and parsimonious demand model. It is flexible because, though it is based on the logit model, it nevertheless allows for a more general pattern of interbrand substitution. This is facilitated by the assumption of correlated preferences across brands. The parsimony stems from the origins in the logit model that require fewer parameters than standard linear or log–log demand systems to characterize the own- and cross-price elasticities across brands. On the supply side, it provides an approach to decomposing the retail price into the wholesale price, the effect of retail competition, unobserved (to the researcher) promotional payments by manufacturers to the retailer, and the effects of retailer-specific objectives related to the store brand. Finally, in terms of estimation, it provides a joint approach to estimating the parameters of the demand model and the retailer pricing equations in an equilibrium framework. In summary, the results of the analysis have implications for manufacturers and retailers, as well as marketing researchers.

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