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Retailers typically engage in some form of price discrimination to increase profitability. In this article, the authors compare the impact on retailer profitability of two price discrimination mechanisms: quantity discounts based on package size (second-degree price discrimination) and store-level pricing or micromarketing (third-degree price discrimination). Whereas the latter has been well addressed in the marketing literature, there is limited empirical research on the use of quantity discounts for price discrimination. Using store-level sales data, the authors estimate a structural demand model, accounting for parameter heterogeneity and price endogeneity. They combine the parameter estimates with a model of retailer pricing to conduct optimal pricing and profitability simulations under several scenarios, ranging from constraining the retailer not to engage in any form of price discrimination to the least restrictive scenario of setting nonlinear price schedules specific to each store. The pricing simulations enable the decomposition of profitability as a result of the different forms of price discrimination. Profits are greatest when retailers combine second- and third-degree price discrimination. The authors find that the ability to engage in second-degree price discrimination contributes more to retailer profitability than does third-degree price discrimination.

An Empirical Analysis of Price Discrimination Mechanisms and Retailer Profitability

Setting prices to consumers is one of the most critical decisions for the retailer and a primary driver of retailer profitability. To increase profitability, retailers typically engage in some form of price discrimination. In practice, retailers often vary prices across stores to exploit demand differences between store trading areas, a strategy commonly referred to as micromarketing or third-degree price discrimination. For example, higher prices are often found in stores that are located in areas with fewer shopping alternatives (Goodman 2003). Recent studies have addressed the issue of setting optimal retail prices on the basis of observed demographic and competitive factors that can be linked to demand characteristics (Chintagunta, Dubé, and Singh 2003; Montgomery 1997).

Another less obvious way for retailers to price discriminate is to offer quantity discounts based on package size (Cohen 2002; Dolan 1987). In the consumer packaged goods industry, several package sizes are offered in categories such as detergents, beer, paper products, peanut butter, and analgesics. The larger sizes of these products, which are identical along all other dimensions (e.g., brand name, ingredients, flavor), are usually offered at a lower per unit price.[1] When the motivation behind designing a nonlinear price schedule is market segmentation, this practice is also known as second-degree price discrimination (Moorthy 1984; Mussa and Rosen 1978).

The focus of this article is on these two mechanisms of price discrimination: micromarketing or store-level pricing (third-degree price discrimination) and quantity discounts based on package size (second-degree price discrimination). Store-level pricing is an effective price discrimination mechanism when observable characteristics provide a signal of consumer price sensitivity and willingness to pay.

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[1]In the grocery industry, there are exceptions in which firms charge quantity premiums so that per unit prices increase with size in categories such as tuna and juices.

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However, after consumers enter a store, there remains significant heterogeneity among customers that the retailer can exploit. Note that though the information necessary to engage in micromarketing (i.e., demographic characteristics of the store's customers) is readily available (e.g., from the Census Bureau), the individual consumer's willingness to pay is unobserved. Because these preferences are unobserved, retailers can offer an array of package sizes, allowing consumers to segment themselves by self-selection of their preferred alternative based on their own willingness to pay.

The objective of this article is to decompose the contribution of these two price discrimination mechanisms (i.e., quantity discounting and micromarketing) to retailer profitability.[2] Under "pure" third-degree price discrimination, prices vary across stores, but per unit prices are the same across package sizes within each store. Under pure second-degree price discrimination, prices are the same across all stores, but per unit prices vary across package sizes. The positive impact on retailer profitability from the "combined" strategy (i.e., varying prices across stores and across sizes within each store) has been well documented in the marketing literature. Montgomery (1997) and Chintagunta, Dubé, and Singh (2003) find profit gains between 4% and 16% when the retailer sets store-level nonlinear price schedules. However, they do not distinguish between the two sources of price differences (i.e., across stores and across sizes).

To our knowledge, the only empirical study that specifically explores the use of package size as a price discrimination mechanism in the consumer packaged goods industry is that of Cohen (2002). Cohen studies nonlinear pricing by the manufacturer in the paper towel industry and finds that a substantial portion of the variation in per unit prices across package sizes can be attributed to price discrimination.

Despite the importance of pricing strategy for retailer profitability, there is limited understanding of the relative efficacy of the price discrimination mechanisms available to the retailer. This is an important issue because each mechanism is distinguished by both the type of information available to the retailer about consumer preferences and the type of heterogeneity in consumer preferences that is exploited. This is also an important managerial issue because the costs involved with each pricing approach should be weighed against the associated profits. Micromarketing requires store-level pricing systems, which entail considerable time and resources to determine and implement. In contrast, a quantity discount schedule that is uniform across all stores is considerably easier to implement. This article attempts to parse out and measure the gains in profitability from each price discrimination approach.

In general, price differences that cannot be accounted for by cost differences are attributed to price discrimination. However, the retailer may be motivated to offer quantity discounts for reasons other than market segmentation. As Chintagunta (2002) demonstrates, store traffic considerations and competition also influence retailer pricing. Quantity discounts may serve as acquisition and retention tools for high-volume customers who purchase large sizes across categories and make an important contribution to retailer revenue. At some grocery chains, this consideration has lead to the institution of "big deals" aisles, which stock only the largest size in each category. There may also be competitive pressures, particularly from mass discounters that offer larger sizes at discounted prices. Special attention may also be given to categories with high volume in the larger sizes. In addition to their importance for store traffic and retailer profitability, these categories may also shape the price image of the store. The combination of these factors may cause the retailer to offer deeper quantity discounts than the price discrimination objective alone necessitates. Although we account for some of these factors in our model development, we focus on price discrimination as the primary motivation for offering quantity discounts.

Our analysis uses data on the over-the-counter (OTC) analgesics category from a large supermarket chain in the Chicago area. The retailer engages in both forms of price discrimination; that is, prices for products vary significantly across stores, and observed retail prices show significant quantity discounts, with the price per tablet decreasing with bottle size. Although the observed quantity discounts may be an indication of second-degree price discrimination by the retailer, they could also be due to cost differences. We demonstrate that a significant proportion of the observed nonlinearity in prices is due to the retailer's pricing decision.

We estimate a category demand model using a random coefficients logit specification. The model allows for heterogeneity in preferences due to both observed and unobserved factors. We use instruments to control for price endogeneity (Besanko, Gupta, and Jain 1998; Villas-Boas and Winer 1999) due to unobserved factors, such as shelf space and product location. We allow for dynamic promotion effects on price sensitivity and promotion response parameters (Foekens, Leeflang, and Wittink 1999). Allowing for parameter dynamics accounts for strategic adjustments in purchasing behavior (e.g., stockpiling; see Van Heerde, Leeflang, and Wittink 2004) following promotions. We combine parameter estimates from the demand model with a model of retailer category profit maximization to simulate optimal prices and profitability under four pricing policies. Comparing profits across pricing policies enables us to decompose profitability into the different sources of price discrimination and understand the relative importance of each for profits.

We organize the rest of the article as follows: In the next section, we present the demand model. Then, we describe the data and the empirical results from the demand estimation. We provide a detailed overview of the retailer's role in setting price and analyze the impact of price discrimination on profitability. Finally, we present our conclusions from the research.

MODEL FORMULATION

We model consumer demand using the aggregate mixed logit model (McFadden and Train 2000), which has been applied in both marketing and economics to estimate demand for differentiated products (e.g., Berry, Levinsohn, and Pakes 1995). The estimation approach allows for parameter heterogeneity and controls for price endogeneity.

We assume that the observed market shares are driven by individual choices. Formally, we assume that consumer i

[2]We do not consider first-degree price discrimination, which involves setting prices according to each person's willingness to pay. In the grocery setting, targeted coupons are one form of this pricing strategy (for an application, see Rossi, McCulloch, and Allenby 1996).

chooses either one of J products in the category or the no-purchase option. The probability that consumer i chooses product j at time t from store s is

$$(1)\quad \Pr_{ijts} = [\exp(\alpha_{ij} + \delta_i s_j + \gamma_i p_{jts} + \tau_i d_{jts} + \eta_i p_{jts} \times d_{jts} + \omega_i CE_{its} + \theta_i DS_{ts} + \xi_{jts})] \Big/ \Big[1 + \sum_{k=1}^{J} \exp(\alpha_{ij} + \delta_i s_j + \gamma_i p_{jts} + \tau_i d_{jts} + \eta_i p_{jts} \times d_{jts} + \omega_i CE_{its} + \theta_i DS_{ts} + \xi_{jts})\Big],$$

where i = 1, …, I; j = 1, …, J; t = 1, …, T; and s = 1, …, S. This depends on the characteristics of product j at time t in store s: size (s_j); price (p_{jts}); an indicator for the presence of a price promotion (d_{jts}); an interaction term between price and the presence of a promotion ($p_{jts} \times d_{jts}$); unobserved (to the researcher) characteristics (ξ_{jts}), such as advertising and coupon availability, which may be potentially correlated with price; and parameters representing consumer I's preference for brand j (α_{ij}), preference for size (δ_i), price sensitivity (γ_i), responsiveness to promotions (τ_i), and the impact of promotion on price sensitivity (η_i). We include characteristics of the competitive environment (CE_{its}) of each store to account for variations in the shopping alternatives that consumers have for making their purchases. Category demand shifters (DS_{ts}) include a seasonal effect and a dummy variable to indicate the presence of a pharmacy in a store.

The model allows for dynamic influences of prior promotions on price sensitivity (γ_i) and promotion response (τ_i) (Foekens, Leeflang, and Wittink 1999). For example, if consumers stockpile and increase inventory because of a deep price discount (Hendel and Nevo 2003; Van Heerde, Leeflang, and Wittink 2004), they may be less sensitive to price in subsequent weeks. We allow the price sensitivity parameter to depend on both the depth and the recency of previous price promotions. Similar to Foekens, Leeflang, and Wittink's (1999) approach, we compute a weighted sum of prior price promotions: $PR_{jt} = \Sigma_{v=1}^{V} v^{-1}(\bar{p}_{j,t-v} - p_{j,t-v})$, where $\bar{p}_{j,t}$ is the regular nonpromoted price, $p_{j,t}$ is the actual price, and v is the weeks of prior price history used to compute the measure (v = 8). The price sensitivity parameter is now a function of an overall mean (γ) and the dynamic impact of recent price promotions (γ_{PP}):

$$(2)\quad \gamma = \bar{\gamma} + \gamma_{PP} PP_{jt}.$$

Similarly, we allow promotion response to depend on the duration since previous promotion (w_j), with the expectation that the longer the duration since previous promotion, the stronger is the response to the promotion (τ_w):

$$(3)\quad \tau = \bar{\tau} + \tau_w \ln(w_j).$$

We also allow for observed and unobserved heterogeneity in the brand preference (α_i), size preference (δ_i), and price sensitivity (γ_i) parameters. The preference parameters are competitor variables, and σ is the standard deviation of the distribution:

$$(4)\quad \begin{bmatrix} \alpha_i \\ \gamma_i \end{bmatrix} = \begin{bmatrix} \bar{\alpha} + \pi_a DM_t \\ \bar{\gamma} + \pi_\gamma DM_t + \omega_\gamma CE_t \end{bmatrix} + \sigma'\varepsilon_i,\ \varepsilon_i \sim N(0, I).$$

We measure package size with dummy variables. Thus, for a category with three sizes, we use two dummy variables, s_{small} and s_{large}, with the medium size as the base. Intuitively, a consumer who has a strong preference for the large size will likely have a weaker preference for the smaller size, and vice versa. We account for heterogeneity in and correlation between preference for size, δ_{small} and δ_{large}, as follows:

$$(5)\quad \begin{bmatrix} \delta_{i,\,small} \\ \delta_{i,\,large} \end{bmatrix} = \begin{bmatrix} \delta_{small} + \pi_{\delta_{small}} DM_t + \varepsilon_{small} \\ \delta_{large} + \pi_{\delta_{large}} DM_t + \varepsilon_{large} \end{bmatrix},\ \varepsilon \sim N(0, \Sigma).$$

The inclusion of demographic factors accounts for correlation in size preference due to observed factors. Correlation in preferences due to unobserved factors is captured by Σ, the variance–covariance matrix.

We aggregate the model specified at the individual level to predict market shares at the store level. The general estimation approach involves finding the parameters for the individual-level model that produce a predicted market share closest to the observed market share (Berry 1994; Nevo 2000). The next section describes the data and the estimation results.

RESULTS

Data

We use data on the OTC analgesics category from the Dominick's Finer Foods chain in the Chicago area over a one-year period. For each store in each week, we observe the number of units sold for each Universal Product Code (UPC), the UPC price, whether it was on price promotion, and the retailer's margin (from which we can compute the wholesale cost). With the transition of prescription-only drugs to OTC nonprescription status (e.g., Advil, Aleve), the analgesics category has gained importance for retailers. Information Resources Inc. reports that in food and mass-market stores, sales of oral analgesics tablets increased 4.5% to $2.73 billion between January 1999 and January 2000. These trends make the analgesics category an important area for expansion for grocery retailers.

For the model estimation, we use 11 products, consisting of four brands (Tylenol, Advil, Bayer, and Store Brand) and three sizes (25, 50, and 100 tablets).[3] The selected UPCs account for 62% of total sales in the category. We provide the descriptive statistics in Table 1.

The market share shows the percentage of bottles sold in each brand size. Tylenol is the market leader, capturing more than 25% of the category volume, and it also has the greatest share in each size group. Notably, no one size appears to be the most popular across all the brands. We compute the price the consumer would pay for 100 tablets in each bottle size. For Tylenol and Bayer, a consumer buying 100 tablets in the smallest size would pay twice as much as a consumer buying 100 tablets in the largest size. Overall, the retailer offers significant quantity discounts, the magnitude of which declines with size. So, for example, the savings are greater if a customer trades up from 25 to 50 tablets than if he or she trades up from 50 to 100 tablets.

[3]The store brand has only two sizes with significant market share: medium and large; thus, our model has 11 products rather than 12. Note that we do not include the extra-large size because of its very low share.

Table 1
DESCRIPTIVE STATISTICS

Brand	*Size (Number of Tablets)*	*Market Share (%)*	*Price per 100 Tablets*	*Cost per 100 Tablets*	*Units Sold on Promotion (%)*
Tylenol	25	8.9	14.08	9.04	1
Tylenol	50	11.1	9.98	7.52	10
Tylenol	100	7.6	7.14	5.93	11
Advil	25	7.3	12.08	8.08	10
Advil	50	5.1	10.38	7.4	19
Advil	100	2.2	8.23	6.25	15
Bayer	25	2.5	10.64	7.6	16
Bayer	50	2.0	7.62	5.34	22
Bayer	100	4.9	4.95	3.73	28
Store brand	50	6.2	4.98	1.92	10
Store brand	100	4.2	3.29	1.51	22

The percentage of units sold on promotion indicates that a greater percentage of the larger sizes is sold on promotion than the smallest size.

In addition to sales information, we use data on the demographic characteristics and competitive environment of each store's trading area. We capture the demographic characteristics of the customer population with the following variables: age60 (percentage of the population that is over the age of 60), ethnic (percentage of the population that is black or Hispanic), HHsize (percentage of households in the store area with five or more members), and homevalue (percentage of houses in the store area valued at more than $150,000). We capture the competitive environment of each store with measures of the distance from the store to different types of competitors: Jewel (the largest supermarket chain in the area), everyday-low-price (EDLP) store, and drugstore. To account for factors that could shift demand, we include an indicator for whether a store has a pharmacy department and a seasonality term for winter months.

There is also cause for concern that some observed variables, particularly price, may be correlated with the unobserved factors (ξ_{jts}). The inclusion of the variable PP_{jts} as an interaction with price also raises some endogeneity concerns because it is likely that there is some serial correlation in ξ_{jts}. Because we use prior prices to compute PP_{jts}, there will likely be a correlation between PP_{jts} and ξ_{jts}. To account for this endogeneity, we construct an instrument that is a weighted function of prior wholesale price, and we compute this in the same way as PP_{jts}. The instrument set also includes wholesale price, package size, and local area demographics.

As we discussed in the "Model Formulation" section, we allow for a no-purchase option to enable category expansion and contraction with changes in the marketing mix. In our data, we observe the number of households that visit each store in each week. From the Information Resources Inc. factbook, we know that, on average, consumers buy analgesics three times a year. We use this information to compute the share of the outside good, such that not all consumers entering the store on a given week are in the market for analgesics.

Demand Model Results

The results of the demand model estimation appear in Table 2. We group the variables into five sets: brand preference, marketing mix, size, demand shifters, and interaction effects. All the brand fixed effects have a negative sign because of the large share of the outside good.[4] We find that Tylenol has the greatest mean preference, which is consistent with its large category share.

The next set of variables is related to the marketing mix. The coefficient on price (–1.18) is negative, as we expected. The standard deviation of the distribution of this parameter (.49) indicates that after we account for sources of observed heterogeneity, there is significant unobserved heterogeneity in price sensitivity. The promotion variable, which we measured as the proportion of units sold on promotion, indicates the presence of a temporary price reduction. Promotions increase the likelihood of purchase. The negative coefficient on the price and promotion interaction (–.04) indicates that consumers are more price sensitive toward promoted items.

The results show some evidence of parameter dynamics. The interaction of price with the measure of recency and depth of prior promotion has a positive coefficient (.18), indicating that the more recent or deeper a promotion, the less price sensitive are consumers. This may also reflect stockpiling effects because consumers are less responsive to price when they have a high inventory. The interaction of promotion with weeks since previous promotion indicates that promotion effectiveness increases the longer time has elapsed since the previous promotion (.05).

The price interaction parameters show that demographic and competitive variables have a significant impact on price sensitivity. The negative coefficients on the price × age60 (–1.3) and price × HHsize (–3.16) interactions indicate that older people and large households tend to be more price sensitive. The positive coefficient on the price × homevalue interaction (.36) indicates that consumers in affluent areas tend to be less price sensitive. The coefficients on the price and competitor interaction terms, drugstore and EDLP, are positive. Because the competitor variables measure the distance from the store, the interpretation of the positive coefficients is that as the distance from a competitor increases, price sensitivity decreases. These results suggest that as the

[4]Because of space considerations, we report only the brand fixed effects. Parameter estimates of the terms related to observed and unobserved heterogeneity are available on request.

Table 2

DEMAND MODEL ESTIMATION RESULTS

	Parameter Estimate	*Standard Error*
Brand Preference		
Tylenol	–2.59*	.38
Advil	–3.02*	.39
Bayer	–4.86*	.25
Store	–3.59*	.22
Tylenol	–2.59*	.38
Marketing Mix		
Price	–1.18*	.14
Price: standard deviation	.49*	.16
Promotion	.13*	.04
Price × promotion	–.04*	.02
Price × recency-depth of prior promotion	.18*	.02
Promotion × ln(weeks since promotion)	.05*	.01
Size		
Small (25 tablets)	1.02*	.17
Small: standard deviation	1.35*	.25
Large (100 tablets)	–3.42*	.14
Large: standard deviation	2.05*	.81
Small large covariance	–1.04*	.41
Demand Shifters		
Winter	.22*	.01
Pharmacy	.04*	.01
Competitive Effects		
Distance to drugstore	–.46*	.11
Distance to EDLP	.03	.21
Distance to Jewel	–.01	.04
Interaction Terms		
Price × age60	–1.30*	.35
Price × ethnic	.70*	.14
Price × HHsize	–3.16*	.8
Price × homevalue	.36*	.1
Price × drugstore	.90*	.32
Price × Jewel	–.65	.92
Price × EDLP	.66*	.16
Small × age60	–.87*	.39
Small × ethnic	.83*	.31
Small × HHsize	–4.12*	1.26
Small × homevalue	–.76	.72
Large × age60	.39*	.09
Large × ethnic	–.70*	.1
Large × HHsize	4.40*	.97
Large × homevalue	.57	.7

* = significance.

availability of shopping alternatives increases in an area, price sensitivity also increases.

We measure the size effect variables relative to the base medium size. We find that consumers prefer the small size the most (1.02) and the large size the least (–3.42); this is also consistent with Cohen's (2002) findings for the paper towel category. The standard deviations for the large size (2.05) and for the small size (1.35) preference parameters indicate the presence of heterogeneity in consumer preferences due to unobserved factors. The negative covariance in preferences for small versus large size (–1.04) indicates that a high utility for the small size implies a lower utility for the large size. Areas with a greater proportion of large households have a greater preference for the large size. Notably, areas with a large ethnic population have a greater preference for the small size, which may be due to the influence of budget constraints on ethnic households.

We include the presence of an in-store pharmacy and a winter dummy variable as category demand shifters. We find that demand for analgesics is greater during the winter season, which is not surprising. We also find that the presence of a pharmacy increases demand for the analgesics category. The finding that the presence of a pharmacy, which is primarily for prescription drugs, also has a spillover effect on OTC drugs is good news for the retailer because more supermarkets are adding a pharmacy department to compete with drugstores and mass discounters (Singh 2003). However, this effect is likely overestimated as a result of the endogeneity of the pharmacy location decision because retailers will open pharmacies in areas with a strong demand for medical supplies.

We also include distances to closest competitors as category demand shifters. We expect that with fewer purchasing venues in an area, the likelihood of not making a purchase will decrease. The negative coefficient on distance to the closest drugstore implies that consumers are more likely to purchase analgesics from the store when there is no drugstore in the area. The coefficients on distance to the closest EDLP store (.03) and Jewel (–.01) supermarket are not significant and are small compared with the coefficient on the drugstore variable (–.46). Given that the category of our analysis is analgesics, it is not surprising that the distance to the closest drugstore is more important in determining the share of the outside good.

The empirical results reveal the following key insights:

- Preference for size varies significantly as a result of unobserved factors, which indicates that offering an array of products with different sizes within each brand can be a useful tool for sorting consumers and capturing differences between consumer segments.
- Consumer price sensitivity varies with observed demographic and competitive factors, indicating an opportunity for third-degree price discrimination by setting store-level prices.
- Preference for different sizes also varies as a result of observed demographic factors, signaling an opportunity to combine second- and third-degree price discrimination by varying the quantity discount schedule across stores.

In the next section, we explore the retailer's pricing strategy and use the parameter estimates from the demand model to investigate the contribution of price discrimination to retailer profitability.

RETAILER PRICING AND PROFITABILITY

Evidence of Retailer Price Discrimination

Observed quantity discounts may be due to either the manufacturer's wholesale price or the retailer's pricing strategy. Typically, quantity discounts that cannot be explained by cost differences are attributed to price discrimination.[5] Because we observe wholesale prices from the manufacturer, we compute the retailer's average margin and

[5]There could also be other labor or shelving costs associated with different sizes, especially in bulkier categories or in products that require refrigeration. However, our assumption of equal costs (except for the manufacturer price) for different sizes is quite reasonable for the analgesics category we use in this empirical analysis because the physical differences across different sizes are relatively small.

Table 3
RETAILER PRICING BEHAVIOR

Brand	*Number of Tablets per Bottle*	*Average Margin per Bottle: p – c ($)*	*Average Markup per Bottle: (p – c)/p (%)*	*NLR (%)*
Tylenol	25	1.26	36	
Tylenol	50	1.23	25	63
Tylenol	100	1.21	17	55
Advil	25	1	33	
Advil	50	1.49	29	60
Advil	100	1.98	24	52
Bayer	25	.76	29	
Bayer	50	1.14	30	25
Bayer	100	1.22	25	32
Store brand	50	1.53	61	
Store brand	100	1.77	54	76

markup per bottle in Table 3. To provide an accurate reflection of the retailer's pricing decision, we compute these numbers using the actual wholesale and retail price per bottle rather than price per 100 tablets.

On average, the margin is the greatest for the large size and the least for the small size, and the markup is greater for the smaller sizes. As we discussed previously, strategic considerations beyond price discrimination may cause the retailer to offer quantity discounts. Although we do not demonstrate the absence of other possible explanations for the observed patterns, the evidence indicates that the retailer uses quantity discounts in a strategic manner that is consistent with price discrimination. In addition, the variation in margin and markups across products and sizes indicates that the retailer is not following a fixed rule of thumb in setting its price relative to wholesale price.

Assuming that other variable costs are equal across products of different sizes, we can precisely account for the proportion of the nonlinearity in retail prices that is due to the retailer's pricing decision. We measure the nonlinearity due to the retailer (NLR; Cohen 2002) as the percentage of the nonlinearity in retail prices (P_{25}–P_{50}) that cannot be accounted for by the nonlinearity of wholesale prices (W_{25}–W_{50}):

$$\text{NLR} = \frac{(P_{25} - P_{50}) - (W_{25} - W_{50})}{(P_{25} - P_{50})}. \tag{6}$$

Table 4 shows that the percentage of the NLR varies between 25% and 75%. On average, approximately 50% of the observed nonlinearity in retail price is due to the retailer's pricing decision.

An examination of prices across stores reveals that the retailer charges different prices for the same product at different stores. For the same data source, Montgomery (1997) and Chintagunta, Dubé, and Singh (2003) report the existence of price zones within which the retailer sets prices. For the analgesics category, we find up to three levels of price in any week.[6]

In some cases, the retailer charges a uniform price across the chain for the smallest size, while varying the price for the larger sizes. In general, it appears that the retailer sets a base price and then makes a percentage adjustment from the base to determine pricing in other zones. Although this pattern does not hold for every UPC, its prevalence implies that when the retailer varies prices over zones, there may be some fixed adjustment rule involved.

Optimal Pricing and Retailer Profitability

Given the evidence that the retailer engages in price discrimination, we decompose the contribution to profitability from each type of price discrimination mechanism.[7] Using the results of the demand estimation, we simulate optimal prices under several scenarios.

We assume that the retailer sets prices to maximize category-level profits, which is consistent with the assumption made in most studies (e.g., Kim, Blattberg, and Rossi 1995; Raju, Sethuraman, and Dhar 1995) and is also in line with the industry trend toward category management. The retailer's costs are the wholesale price paid to the manufacturer for each product (w_j) and a fixed overhead cost (F) of maintaining the category. The retailer's problem is to determine the price of each product in the category in every week to maximize category profits:

$$\prod = \sum_{j \in J} (p_{jt} - w_{jt})Q_{jt} - F. \tag{7}$$

Given the wholesale prices and parameter estimates from the demand model in Equation 1, we can solve for the full vector of optimal retail prices (p*), which maximizes Equation 7.

Shifts in the retailer's pricing policy may lead to a response from the competition and strategic adjustments in consumer behavior, and it may have implications for customer store loyalty. To allay these concerns, previous research has imposed constraints on the optimization problem. Chintagunta, Dubé, and Singh (2003) require that optimal prices do not decrease consumer welfare. Montgomery (1997) requires that average prices and revenues do not increase. Similarly, we impose the constraint that the share weighted average price does not increase with the suggested optimal prices. For chain-level pricing, we use the observed

[6]The number of price zones has increased over time. Using data from a later time period, Chintagunta, Dubé, and Singh (2003) find up to 16 price zones.

[7]Note that we focus on the short-term objective of price setting and take the array of product offerings as a given. Although the product assortment decision is also an endogenous variable, we believe that these are long-term decisions.

Table 4
IMPACT OF DIFFERENT PRICING POLICIES ON PROFITABILITY

	Average Weekly Store Profit in Thousands of Dollars (Standard Error)	*Change in Profits (Standard Deviation) from Switching to (%)*			
		Chain Uniform	*Chain Nonlinear Pricing*	*Store Uniform*	*Store Nonlinear Pricing*
No Price Discrimination					
Chain uniform	67 (9)	—	26 (9)	10 (9)	34 (10)
Second Degree Only					
Chain nonlinear	86 (10)	–21 (5)	—	–13 (2)	6 (3)
Third Degree Only					
Store uniform	73 (10)	–9 (2)	15 (2)	—	21 (5)
Second and Third Degree					
Store nonlinear	92 (11)	–25 (5)	–5 (2)	–18 (4)	—
Current Pricing Policy					
Actual	75 (10)				
Optimized	87 (11)				

share weighted average price at the chain level (p_c) to constrain the optimal share weighted (s_j) average price paid:

$$\sum_{j \in J} p_j^* s_j(p^*) \leq \bar{p}_C. \tag{8}$$

For the store-level pricing scenarios, we compute the share weighted observed price for each store (p_S) and impose the constraint at the store level.

We compute optimal prices and the implied profits under the following pricing scenarios:

- *Chain uniform (no price discrimination)*: The per unit price for each brand is constant across sizes and stores. There are no quantity discounts or variation in prices across stores.
- *Chain nonlinear (pure second-degree price discrimination)*: The firm sets a quantity discount schedule that is the same for all stores.
- *Store uniform (pure third-degree price discrimination)*: The firm can vary prices across stores but does not offer quantity discounts. For each store, the firm determines a per unit price, which is the same for all sizes.
- *Store nonlinear (combined second- and third-degree price discrimination)*: The firm can set quantity discount schedules for each store.

This exercise enables us to decompose profitability into the different sources of price discrimination and understand the relative importance of each for profits. Table 4 shows average weekly profits for the chain under the different pricing scenarios. The differences in profit outcomes are statistically significant at the .05 level and are economically significant. For each scenario, we also report the percentage difference in profits compared with other scenarios. For reference, we also report the actual profits and the expected profits (if the firm were to set optimal prices) under the firm's current pricing policy. Note that expected profits under the firm's current pricing policy are equal to profits from setting a single nonlinear price schedule across the chain, which is consistent with Chintagunta, Dubé, and Singh's (2003) approach.

Comparing profits across scenarios shows that there are significant gains from the ability to set nonlinear prices and to vary prices across stores. If a store were to change from chain-level uniform pricing, the most restrictive policy, to store-level nonlinear pricing, the least restrictive policy, profits would increase by 34%. The decomposition shows that the increase in profits from nonlinear pricing (26%) is significantly greater than the increase from store-level pricing (10%). If the firm were to set one chain-level nonlinear price schedule, profits would increase by 26% compared with the chain-level uniform price schedule. Conversely, if the firm were to set uniform store-level prices, profits would increase by 10% compared with chain-level uniform pricing. After the firm has set a chain-level optimal nonlinear price schedule, moving from chain-level nonlinear pricing to store-level nonlinear pricing increases profits by an additional 6%. Overall, the results reflect the importance of pricing flexibility to the firm's profit. The critical finding of this analysis is that the firm's ability to offer quantity discounts based on package size contributes more to its profitability than does its ability to vary prices across stores.

CONCLUSION

We investigate the impact of price discrimination mechanisms on retailer profitability through a comparison of the contribution to profits from quantity discounts based on package size versus store-level pricing. We find that an optimal quantity discount schedule set at the chain level contributes more to profitability than does setting store-level prices without quantity discounts. The key insight here is that quantity discounting adequately captures a larger proportion of the heterogeneity in demand than does store-level pricing. In practical terms, setting a quantity discount schedule at the chain level leads to a significant increase in profits and is also much easier to implement than setting store-specific prices. The results suggest that managers can focus on the simpler task of setting quantity discount schedules to increase profits before investing in store-level pricing systems. Although the combination of store-level pricing and quantity discounts contributes significant incremental profits, there a many complications involved in implementing store-level pricing.

Note that the relative efficacy of each type of price discrimination mechanism depends on the nature of consumer preferences and whether the retailer has information or signals about these preferences. For quantity discounts to serve as an effective price discrimination mechanism, it is important that people differ in their valuation of additional volume of the product and that the retailer has information on the distribution of willingness to pay. For example, if all consumers have limited consumption of a product in general, using quantity discounts based on package size will not be an effective segmentation mechanism.

The effectiveness of third-degree price discrimination depends on whether the observed characteristics used for segmentation concurrently segment consumers on the basis of their willingness to pay. Attempts to relate preference and price sensitivity parameters to demographic and competitive variables have yielded mixed results. Some research has found evidence of a relationship between price sensitivity and observed demographics (Hoch et al. 1995), which can be exploited for pricing purposes. However, the majority of previous research has found demographic characteristics to be poorly correlated with preference parameters (Elrod and Winer 1982; Rossi and Allenby 1993). For this reason, it is not surprising that second-degree price discrimination outperforms third-degree price discrimination. The combination of second- and third-degree price discrimination will yield greater profits. However, the increase in profits will be greater when preferences for size can be related to observed demographic characteristics, allowing retailers to vary the shape of the nonlinear price schedule according to local preferences.

Our research focus is on comparing price discrimination mechanisms rather than on prescribing an approach for determining optimal prices. The retailer's optimal pricing decision also depends on its interaction with the manufacturer, which also sets a nonlinear price schedule to the retailer. The relative power of the retailer with respect to the manufacturer (Kadiyali, Chintagunta, and Vilcassim 2000) affects the retailer's ability to use quantity discounts for price discrimination and the division of profits from price discrimination. In terms of pricing-decision support, manufacturers tend to have better resources than retailers, which enables manufacturers to make better pricing decisions. As the manufacturer uses quantity discounts more effectively, the retailer must rely more on store-level pricing as its primary price discrimination mechanism. In addition, we do not account for the variation in pass-through of trade promotions (Besanko, Dubé, and Gupta 2005), which also depends on the retailer's interaction with the manufacturer. The logical next step is to address these issues with a unified structural framework that accounts for both the supply side and consumer demand.

The assortment of product sizes to offer is also an important aspect of the retailer's decision. For example, supermarket chains do not carry the very large sizes that are available at mass discounters. Because the retailer can use the product assortment as part of the segmentation strategy by varying product selection across stores, it would be worthwhile to investigate how the optimization of product assortment at the store level affects profitability. Israilevich (2004) considers the retailer's product assortment decision in the bath tissue category, accounting for consumer demand and manufacturer payments. He shows that slotting allowances enable the retailer to offer a wider product assortment than would be profitable without the payments. This result further emphasizes the notion that recommendations for the retailer's optimal behavior should consider the impact of both consumers and manufacturers.

A limitation of this article is that though the consumer demand model allows for dynamics, the retailer pricing model does not. It is likely that if consumers adjust demand strategically, the retailer will also incorporate expectations about future demand changes when it sets current price. This would be better captured by allowing for dynamic retailer pricing, such that the retailer would choose a sequence of optimal prices over time. Although we believe that allowing for dynamic retailer pricing will not have an impact on the substantive results of our research directionally, we expect that there will be an impact on the shape of the nonlinear price schedules over time. Appropriately incorporating dynamics in both the consumer demand and the retailer pricing models presents an avenue for further research.

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