

# Own-Brand and Cross-Brand Retail Pass-Through

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In this paper we describe the pass-through behavior of a major U.S. supermarket chain for 78 products across 11 categories. Our data set includes retail prices and wholesale prices for stores in 15 retail price zones for a one-year period. For the empirical model, we use a reduced-form approach that focuses directly on equilibrium prices as a function of exogenous supply- and demand-shifting variables. The reduced-form approach enables us to identify the theoretical pass-through rate without specific assumptions about the form of consumer demand or the conduct of a category-pricing manager. Thus, our measurements of pass-through are not constrained by specific structure on the underlying economic model. The empirical pricing model includes costs of all competing products in the category on the right-hand side (not only the cost of the focal brand) and yields estimates of both own-brand and cross-brand pass-through rates.

Our results provide a rich picture of the retailer's pass-through behavior. We find that pass-through varies substantially across products and across categories. Own-brand pass-through rates are, on average, more than 60% for 9 of 11 categories, a finding that is at odds with the claims of manufacturers about retailers in general. Importantly, we find substantial evidence of cross-brand pass-through effects, indicating that retail prices of competing products are adjusted in response to a change in the wholesale price of any given product in the category. We find that cross-brand pass-through rates are both positive and negative. We explore determinants of own-brand and cross-brand pass-through rates and find strong evidence in multiple categories of asymmetric retailer response to trade promotions on large versus small brands. For example, brands with larger market shares, and brands that contribute more to retailer profits in the category, receive higher pass-through. We also find that trade promotions on large brands are less likely than small brands to generate positive cross-brand pass-through, i.e., induce the retailer to reduce the retail price of competing smaller products. On the other hand, small share brands are disadvantaged along three dimensions. Trade promotions on small brands receive low own-brand pass-through and generate positive cross-brand pass-through for larger competing brands. Moreover, small share brands do not receive positive cross pass-through from trade promotions on these larger competitors. We also find that store brands are similarly disadvantaged with respect to national brands.

*Key words:* pricing; promotion; retailing; channels of distribution; econometric models

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## 1. Introduction

In the packaged goods industry, over 60% of manufacturers' marketing budgets is now channeled through the retailer in the form of trade promotion spending (Cannondale Associates 2001). This amounts to 16% of the revenues of these manufacturers. The annual Cannondale survey shows that year after year, the single biggest concern of manufacturers is the inefficiency of this trade promotion spending. Manufacturers believe that "nonpass-through" of trade-promotion money to consumers is a major contributor to the inefficiency. They contend that only about half of their trade spending is passed through to the consumer, while retailers claim that percentage

is substantially higher. In the 2001 Cannondale survey, for example, food manufacturers claimed that 52% of trade funds were passed through to consumers, 21% covered retailers' promotion costs, and 27% were applied to the bottom line of the retailer. By contrast, food retailers said they passed through 62%, used 24% to cover promotion costs, and 14% went to the bottom line. Based on the estimated trade-promotion expenditure of \$75 billion, the gap between manufacturers' and retailers' reported amounts of pass-through exceeds \$7.5 billion.

Retailers mediate the marketplace impact of trade promotions, which are a key competitive instrument for manufacturers. Hence, it is essential for

manufacturers to understand retail pass-through behavior. Our goal in this paper is to describe the pattern of pass-through of a major Chicago supermarket chain. For our analysis we use a scanner data set for 11 product categories that includes weekly retail shelf prices and wholesale prices. Data on the latter are rarely available for academic studies. For each of the stores in the chain, we also have a set of characteristics that describes the consumers and the local competition in the store's trading area. In each product category, we estimate own-brand and cross-brand pass-through elasticities for each of the brands. Pass-through is defined as the rate at which changes in the wholesale price of a product are passed through by the retailer to the shelf prices. To measure pass-through, we use the reduced form of a retail-pricing model as the basis of our econometric specification. This reduced-form approach permits us to estimate pass-through without constraints on the range of pass-through that are implicit in a structural model. The econometric model controls for the potential role of multiproduct pricing decisions by a category manager. Thus, we consider the impact of changes in a given brand's wholesale price on the shelf prices of both, the same product, and all other products in the category.

This paper has two primary objectives—one descriptive and the other exploratory. The descriptive component documents the magnitudes of own-brand and cross-brand pass-through elasticities and rates in several large supermarket categories. As we discuss below, there is little published evidence on retail pass-through, especially on cross-pass-through rates. We find that many of our results would not be predicted by extant theoretical models. This suggests there is a need and opportunity for marketing scientists to develop more general theoretical models of retail pass-through.

Given the broad range of pass-through rates that we discover across products and categories, we carry out an exploratory second-stage analysis. Here we examine the determinants of own-brand and cross-brand pass-through elasticities across products and across retail stores. The set of covariates we examine includes market share, share of category profits, store brands versus national brands, and demographic and competitive characteristics of the stores' trading areas. Our results reveal patterns of covariation that may be used to assess the plausibility of theoretical models of retail pass-through.

### 1.1. Comparison with Previous Empirical Studies of Retail Pass-Through

The importance of trade promotions for manufacturers and retailers has motivated a number of academic studies in marketing. However, in contrast with the

substantial empirical evidence on consumer response to retail promotions, there are only a few empirical studies that study retail pass-through, which is a measure of retailer response to manufacturer trade promotions. Specifically, we find three studies<sup>1</sup> that provide estimates of retail pass-through: Chevalier and Curhan 1976, Walters 1989, and Armstrong 1991. These papers provide valuable insights into the magnitude and range of retail pass-through rates. However, there are important differences between our approach and the methodology employed by past studies.

First, unlike the econometric approach used in this paper, past studies are typically based on *accounting* measures of pass-through. The approach used in these studies is to identify trade promotion events and compute the ratio of retail price change to wholesale price change during this event. This creates potential problems. For example, price changes that occur outside the predefined window of the event are ignored when in fact, due to inventorying behavior, the impact of cost changes may spill over outside the trade promotion event. Further, the reported pass-through is confounded by alternative drivers of retail price changes, such as seasonality. Our use of an econometric model and pooled cross-section, time-series data alleviates these concerns.

Another critical difference is that we model the retail pass-through decision in the context of category management by the retailer, while previous empirical studies of retail pass-through consider each product independent of other products in the category. In effect, therefore, past work makes the (unstated) assumption that cross-brand pass-through rates are zero.<sup>2</sup> Our model of retail pass-through allows the wholesale prices of one brand to influence the retail prices of all products in the category. This aspect of our model has two important implications. First, estimates of own-brand pass-through rates are biased if competitive costs are not controlled, because trade promotions on competing products are likely to be correlated due to strategic manufacturer interactions. We provide evidence of this bias in the paper. Second, there are significant cross-brand pass-through effects that indicate the retailer's pass-through is not only on the trade-promoted brand but is also on competing brands in the category. Our analysis, therefore, provides a more comprehensive and accurate picture of retail pass-through.

<sup>1</sup> We discuss the theoretical literature on retail pass-through in a later section, entitled "Pass-Through Results from Structural/Theoretical Models."

<sup>2</sup> Literature in product-line pricing (e.g., Reibstein and Gatignon 1984) recognizes the dependence of optimal prices on cross costs for a multiproduct monopolist.

## 1.2. Preview of Findings

We conduct our analysis on 78 products in 11 product categories across 15 price zones. We find that although category average own-brand pass-through rates<sup>3</sup> range from as low as 22% for toothpaste, to as high as 558% for beer, on average the estimated pass-through rates for this chain are much higher than the percentage claimed by manufacturers in the Cannondale (2001) study for all retailers. There are substantial differences in pass-through estimates across retail pricing zones and categories, and between products within categories. We find that the vast majority of own-brand pass-through estimates are positive. As many as 14% of the own-brand pass-through rates are significantly greater than one, implying that in these cases, on average the retailer offers a larger discount to the consumer than the retailer receives from the manufacturer. These findings challenge the “empirical generalization” that *most* products display pass-through much smaller than one (Blattberg et al. 1995), although our results are consistent with empirical findings of Armstrong (1991) and Walters (1989). A notable finding from our analysis is that as many as two-thirds of the estimated cross-brand pass-through rates are statistically significant. This implies that the retailer responds to a trade promotion for one brand by changing retail prices of multiple products in the category. Interestingly, the cross-pass-through effects of a given brand’s wholesale price change are positive for some competing products in the category, and negative for others.

We explore the determinants of pass-through via a pooled analysis across categories of estimated own-brand and cross-brand pass-through rates. In multiple categories we find evidence that the retailer’s pass-through response on large versus small brands is asymmetric. Larger brands, as measured by share of category volume or by share of category profits, receive higher pass-through. Moreover, these brands are unlikely to generate positive cross-brand pass-through, i.e., induce the retailer to reduce prices of competing smaller brands. Conversely, manufacturers of small brands suffer three disadvantages in competing with larger brands in terms of pass-through of trade-promotion dollars to retail price. They receive smaller own-brand pass-through of their trade promotions, the impact of their promotions may be diluted by retail price reductions of their larger competitors, and trade promotions on competing large brands do not induce the retailer to reduce the retail

price of smaller brands. We find that the same three disadvantages accrue to manufacturers of private-label brands relative to national brands.

Higher own-brand pass-through on larger brands is consistent with the belief that promotions on these brands create substantial short-term category expansion and that these brands are important for retailers’ competitiveness. Asymmetries in pass-through rates can also be attributed to disparities in the strength of the bargaining power of manufacturers of large relative to small brands, and national brand manufacturers relative to private-label manufacturers. These disparities in pass-through rates highlight an important competitive advantage in the management of price competition that would be enjoyed by large brands and national brands, relative to small brands and private labels.

The rest of this paper is organized as follows. In §2 we derive a reduced-form econometric model of retail pass-through, and we compare our proposed approach with an alternative structural modeling approach. In §3 we describe the data. In §4 we provide results on own-brand and cross-brand pass-through elasticities and characterize the variation in these results. We summarize and conclude in §5.

## 2. Modeling Retail Pass-Through

We focus on the determination of retail prices in a given product category. In our data, stores from a single supermarket chain in a city are partitioned into zones, with retail prices varying across zones. Therefore, to eliminate concerns with aggregation bias (Christen et al. 1997), we conduct our pass-through analysis at the price zone level, rather than the chain level. Given this focus on zone-level retail decisions, we treat wholesale prices as exogenous because we do not expect the actions of stores in any single price zone to have a strategic impact on manufacturers’ behavior.<sup>4</sup>

In particular, we assume that each price zone  $z$  faces a system of demand functions for the  $J$  products in the category

$$Q_j = D_j(\mathbf{P}, \boldsymbol{\delta}), \quad j = 1, \dots, J, \quad (1)$$

where  $\mathbf{P}$  is the vector of retail prices of the  $J$  products in the category,  $Q_j$  is the quantity demanded of product  $j$ , and  $\boldsymbol{\delta}$  is a vector of exogenous factors

<sup>3</sup> The own-pass-through rate is the proportion of a unit (\$) reduction in the wholesale price per unit that is passed through as a change in the retail price per unit. Analytically, the rate is measured as  $\partial P / \partial C$ , where  $P$  and  $C$  are the retail and wholesale prices per unit, respectively.

<sup>4</sup> We justify this assumption in two ways. First, several empirical studies find support for Stackelberg models in which retailers set retail prices conditional on the wholesale price (Sudhir 2001, Cotterill and Putsis 2001). Second, the Robinson-Patman Act requires that wholesale prices should be common across retailers in a market. Thus, the equilibrium wholesale prices should reflect aggregate market demand conditions rather than the demand conditions facing a subset of stores of a retail chain.

influencing demand.<sup>5</sup> The retailer may adopt a variety of approaches to set prices for the  $J$  products in the category. In general, the vector of optimal prices corresponding to a specific category-pricing model can be represented in reduced form:

$$P_j^* = P_j^*(\mathbf{C}, \boldsymbol{\delta}), \quad j = 1, \dots, J, \quad (2)$$

where  $\mathbf{C}$  is the vector of wholesale prices of all products in the category and  $\boldsymbol{\delta}$  are the exogenous zone-specific demand-shifting variables.

Note that Expression (2) can accommodate many possible interpretations of retailer behavior, including category profit maximization and brand profit maximization. In §2.2, we illustrate how assuming a specific pricing conduct or imposing a parametric form for demand in (1) may induce tight restrictions on the range of observable pass-through rates. Totally differentiating the system of reduced-form pricing relationships in (2) with respect to a change in the marginal cost of a particular product  $i$  yields a set of equilibrium pass-through rates,  $dP_1^*/dC_i, \dots, dP_i^*/dC_i, \dots, dP_J^*/dC_i$ , where  $dP_i^*/dC_i$  is the own-brand pass-through rate, and  $dP_j^*/dC_i$ ,  $j \neq i$  is the set of  $(J - 1)$  cross-brand pass-through rates. These equilibrium pass-through rates incorporate the *full* response of prices to an exogenous change in the cost of product  $i$ . That is, they reflect the retailer's optimal response in terms of prices of all products, taking into account the interdependencies between the products. Moreover, we are able to identify pass-through directly from (2) without assuming a specific form for demand (1) or the nature of pricing decisions.

The derivation above suggests two approaches to building an econometric specification for estimating the pass-through rates: a structural approach or a reduced-form approach. Given our objective of measuring and describing pass-through rates for a large number of products and categories, we prefer a reduced-form approach that estimates the system (2) directly. Alternatively, we could have adopted a structural approach whereby we specify a parametric system of consumer demand equations (1) along with a particular form of retailer pricing conduct. We would then derive the corresponding equilibrium prices (2) and differentiate the system to obtain pass-through (e.g., Goldberg 1995). The structural approach enables the researcher to disentangle the demand versus supply determinants of pass-through. In the absence of precise cost information, the approach may also enable the researcher to infer costs from the underlying model structure. However, the particular structural assumptions one makes about demand and

supply impose restrictions on the magnitude and range of estimated pass-through rates. In §2.2 below we summarize some of the structural assumptions that have been explored in the literature, and their implications for pass-through rates.

## 2.1. Reduced-Form Econometric Models

Our econometric model follows directly from the equilibrium pricing equations in (2) and is specified as the reduced form:

$$P_i = P_i^*(C_i, \mathbf{C}_{-i}, \boldsymbol{\delta}), \quad i = 1, \dots, J. \quad (3)$$

The pass-through rates of interest are derivatives of this reduced-form pricing equation. We estimate a log-linear specification of (3):

$$\ln(P_i) = \alpha_0^I + \alpha_i^I \ln(C_i) + \boldsymbol{\beta}_{-i}^I \ln(\mathbf{C}_{-i}) + \zeta_i^I, \quad (4)$$

where  $\zeta_i^I$  is a mean-zero error capturing aspects of retail pricing that are unobserved (to the econometrician). To check the sensitivity of our pass-through estimates to model specification, we also estimate a linear specification of (3),

$$P_i = \alpha_0^{II} + \alpha_i^{II} C_i + \boldsymbol{\beta}_{-i}^{II} \mathbf{C}_{-i} + \zeta_i^{II}, \quad (5)$$

as well as a more flexible polynomial specification of (3), given by

$$P_i = \alpha_0^{III} + \alpha_i^{III} C_i + \phi_i C_i^2 + \theta_i C_i^3 + \boldsymbol{\beta}_{-i}^{III} \mathbf{C}_{-i} + \zeta_i^{III}. \quad (6)$$

Both the linear and polynomial models relax the constant elasticity assumption inherent in the log-linear model. Additionally, the polynomial model allows for greater curvature in the pricing model and possible nonmonotonicity in pass-through.

An important feature of each specification is the inclusion of the wholesale prices of all products within the category as determinants of the price of product  $i$ , not only the cost of product  $i$ . Note that excluding the wholesale prices of competing brands from the regression model in (4) implies a residual of  $\boldsymbol{\beta}_{-i}^I \ln(\mathbf{C}_{-i}) + \zeta_i^I$ , which may be correlated with  $\ln(C_i)$  due to manufacturer competition. This correlation will bias the estimated value of  $\alpha_i$ , where the direction of the bias will depend on the joint distribution of wholesale prices, and on the signs of  $\boldsymbol{\beta}_{-i}^I$ .

For the particular case of the log-linear specification (4), the parameters  $\alpha_i$  and  $\boldsymbol{\beta}_{-i}$  are interpretable as elasticities. The parameter  $\alpha_i$  is the own-brand pass-through elasticity—a 1% change in the cost of product  $i$  would be associated with a  $\alpha_i$  percent change in its retail price. Similarly,  $\boldsymbol{\beta}_{-i}$  is the cross-brand pass-through elasticity—a 1% change in the cost of a product other than  $i$  would be associated with a  $\boldsymbol{\beta}_{-i}^{\%}$  change in the price of product  $i$ .

<sup>5</sup> The subscript for zone is suppressed in this section for convenience.

## 2.2. Pass-Through Results from Structural/Theoretical Models

Existing pricing theory does not provide a consistent set of predictions regarding retail pass-through. Retail category management involves the complex task of jointly setting prices for an array of products. Unfortunately, very little is known in general about the comparative statics of such a multiproduct price-setting firm. Extending the results of Bulow and Pfleiderer (1983), Tyagi (1999) shows that for a single-product monopolist manufacturer selling through a monopolist retailer, the pass-through rate depends on the concavity of the demand function. For example, the linear, homogeneous logit, and other concave demand functions generate pass-through rates strictly less than one, while the constant elasticity demand function generates a pass-through rate strictly greater than one. Other research finds that the cross-pass-through rate is also highly sensitive to the form of the demand function.

In Table 1 we summarize results on equilibrium pass-through rates in the literature. Note that the assumed model of pricing and the retail channel also imposes constraints on the pass-through. In the context of the logit demand system, a vertical Nash equilibrium in wholesale and retail prices implicitly conjectures a pass-through rate  $dP_i^*/dC_i$  of one and a cross-pass-through rate  $dP_j^*/dC_i$  of zero (e.g., Besanko et al. 1998). In contrast, a vertical Stackelberg equilibrium in wholesale and retail prices, whereby

the manufacturers move first, generates an own-brand pass-through rate between zero and one that is inversely related to a brand's market share (Sudhir 2001). Cross-brand pass-through may be negative if the retailer maximizes category profits, or positive if the retailer maximizes brand profits. In the former case, cross-brand pass-through is decreasing in the share of the trade-promoted brand, whereas in the latter case, cross-brand pass-through is unrelated to brand share.

Other demand models also have specific implications for pass-through rates. If the demand function is linear and the retailer maximizes category profits in a manufacturer Stackelberg game, the own-brand pass-through rate is positive and less than one. Cross-brand pass-through rates depend on the substitutability of the products. In a two-product market, if cross-price slopes of demand are symmetric, then cross-brand pass-through will be zero. However, if the cross-price slopes are asymmetric, then cross-brand pass-through will be positive for one product and negative for the other (Shugan and Desiraju 2001), depending on the direction of asymmetry. Note that this is in contrast with the logit model, where the sign of the cross-brand pass-through effect is a consequence of whether the retailer maximizes category profits or brand profits.

Moorthy (2005) provides a general formulation of the pass-through problem in which the retailer not

**Table 1 Selected Structural Modeling Results on Retail Pass-Through in Marketing**

Paper	Demand model	Vertical strategic interaction	Retailer conduct	Implications for own-brand pass-through ( $\partial P_i/\partial w_i$ )	Implications for cross-brand pass-through ( $\partial P_j/\partial w_i$ )
Besanko, Gupta, and Jain (1998)	Homogeneous logit	Vertical Nash	Maximize category profits	• Equal to 1	• Equal to 0
Sudhir* (2001)	Homogeneous logit	Mfr. Stackelberg	Maximize category profits	• Between 0 and 1 • Inversely proportional to own share $s_i$	• Between 0 and $-1$ • Magnitude is directly proportional to promoting brand share $s_j$ • Unrelated to $s_j$
Sudhir* (2001)	Homogeneous logit (two brands + outside good)	Mfr. Stackelberg	Maximize brand profits	• Positive • Inversely related to own share $s_i$	• Positive • Inversely related to promoting brand share $s_j$ • Directly related to $s_j$
Shugan and Desiraju (2001)	General linear	Not specified	Maximize category profits	• Between 0 and 1 • Does not vary with share	• 0 if cross-price effects in demand are equal • Positive or negative, depending on direction of asymmetry in cross-price effects in demand • In a product pair cross-brand pass-through rates have opposite signs
Moorthy (2005)	Hotelling-like model, with two mfrs and two retailers		Maximize category profits	• Positive	• Positive or negative

\*The conclusions in these two rows are based on analysis of Table 3 in Sudhir (2001).

**Table 2** Descriptive Statistics of Data from 11 Product Categories

Category	No. of products	% Category sales covered	Standardized unit size	Average retail price* (\$)	Average wholesale price* (\$)	Store brand share of units sold
Bath tissue	6	62	4 rolls	1.51	1.33	0
Beer	7	60	6 pack	3.62	3.05	0
Crackers	7	62	16 oz.	2.57	1.80	0.09
Dish detergent	11	60	22 oz.	1.43	1.17	0.07
Frozen orange juice	5	73	12 oz.	1.42	0.93	0.32
Laundry detergent	12	61	64 oz.	3.92	3.26	0
Oat cereal	3	63	1 pack	1.74	1.35	0
Paper towels	6	67	1 roll	0.86	0.71	0.18
Refrigerated orange juice	7	61	64 oz.	2.16	1.56	0.29
Toothpaste	10	60	6.4 oz.	2.37	1.79	0
Tuna, canned	4	60	6.12 oz.	0.72	0.51	0.19
Total	<b>78</b>					

\*Per standardized unit, share weighted.

only maximizes category profits but also competes with other retailers. He shows that in this model the cross-brand pass-through effect can be either positive or negative. He illustrates this finding in two specific demand formulations—a linear demand model and a nested logit model. In the linear demand model, pass-through depends only on demand function slopes, whereas in the nested logit model pass-through is determined completely by equilibrium market shares.

To summarize, our review of the analytic modeling literature reveals that specific theoretical assumptions about demand and supply drive own-brand and cross-brand pass-through rates and their relationship with market share. In practice, therefore, it may be difficult to use structural models without specific constraints on possible pass-through rates. Because our objective is to develop generalizations about pass-through behavior across many products and categories, structural modeling is not a viable or desirable strategy. Our approach (described in §2.1 previously), therefore, is to derive a set of reduced-form pricing equations that allow us to remain agnostic about the form of demand and about retailers' conduct.

### 3. Empirical Analysis

#### 3.1. Data Description

Our data come from Dominick's Finer Foods (DFF), which is the second-largest supermarket chain in Chicago, with approximately 20% market share. We have available retail prices and wholesale prices from 83 stores for 52 weeks in 1992. Data from 11 product categories are analyzed: bathroom tissue, beer, canned tuna, crackers, dish detergents, frozen juice, laundry detergents, oatmeal cereal, paper towels, refrigerated orange juice, and toothpaste. These categories are selected because they span both food and non-food items, as well as because a reasonable number of products (brand sizes) account for at least 60% of category volume. The number of included products

varies from 3 to 12 across the 11 categories, providing a total of 78 products. Although the original data are available at the UPC level, analysis of UPC-level data is difficult because of the large number of UPCs in each category. We aggregate UPCs to form products by selecting UPCs whose prices are (almost) identical and move closely together (correlations in excess of 0.80). In the Dominick's data when no units of an SKU are sold in a particular store, the wholesale and retail prices are recorded as zeros. We remove those store-weeks from the data.

Descriptive statistics of the data are shown in Table 2. The set of 11 categories includes those with relatively low price per standardized purchase unit, such as canned tuna and paper towels, and products with high price per standardized purchase unit, such as laundry detergents and beer. Five of the eleven categories include one or more store brands in the set of products, resulting in a total of eight store brand products. Note that the share of the store brands varies considerably across categories.

We supplement the store data on retail prices and costs with demographic characteristics of the trading area of each store, and variables that characterize the competitive environment facing a store (these variables are discussed in §4.2). The demographic data, obtained by the University of Chicago from Marketing Metrics, are derived from census block data in 1990. See Hoch et al. (1995) for details.

Analysis of retail pass-through depends critically on information about wholesale prices. A unique characteristic of the DFF data is that retail price and profit margin (on retail price) for each UPC and week are included. Subtracting the retail margin from the retail price yields the wholesale price in each week. The measure of wholesale price reflects the average acquisition cost (AAC) of items in inventory.<sup>6</sup>

<sup>6</sup>Kieso and Weygandt (1998) provide a good description of the Average Cost method of inventory valuation.

Peltzman (2000) provides the following definition of average acquisition cost in the Dominick's data:<sup>7</sup>

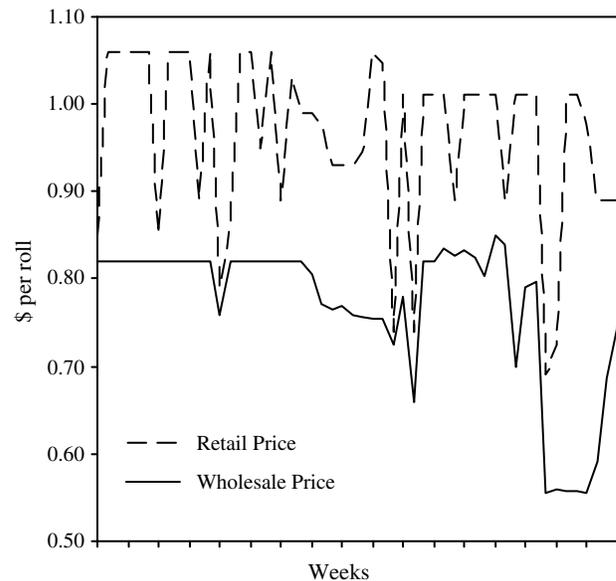
$$\begin{aligned}
 AAC(t) = & \{(\text{Purchases in } t) * \text{Price paid}(t) \\
 & + [(\text{Inventory at end of } t-1) - (\text{Sales in } t)] \\
 & * AAC(t-1)\} * (\text{Inventory at end of } t)^{-1}.
 \end{aligned}$$

Thus, average acquisition cost in week  $t$  is a weighted average of the price that the retailer paid in week  $t$  and the average acquisition cost in the previous week. Peltzman points out that a potential problem with such a measure is sluggish adjustment. Thus, if Dominick's holds large inventories of product purchased at regular wholesale prices, then the downward impact of a trade promotion on costs will be only gradually reflected in the average acquisition cost, as inventories of regularly priced stock are depleted. In this case, the reduction in wholesale prices would be biased downward, with the result that our estimates of pass-through would be too large. Fortunately, there are two mitigating factors that counteract sluggish adjustment. First, Chevalier et al. (2003) notes that DFF's optimal inventory management typically results in trade promotions reflecting quickly in acquisition costs. Second, retailers often know manufacturers' trade-promotions calendar several weeks in advance. As a result, they manage purchasing such that they deplete regularly priced stock before the onset of a trade promotion.

Graphs of costs and prices support this idea—costs typically drop sharply to the lowest point of the trough, although exceptions do occur, albeit infrequently. As an example, we show in Figure 1 weekly retail price and wholesale price for one product—Bounty paper towels—for one store. The graph indicates that most of the variation in retail price is promotional in nature; there appear to be only two “regular” prices of Bounty during this one-year period, and prices are reduced from the regular price frequently. Many, but not all, of these price reductions appear to correspond with wholesale price reductions of Bounty.

Hoch et al. (1995) report that Dominick's practices zone pricing, whereby everyday prices vary across stores in different zones. The data contain an index that classifies the 83 stores into 15 zones.<sup>8</sup> Our analysis indicated that retail prices varied across stores in

**Figure 1** Retail Price and Wholesale Price of Bounty Paper Towels in Store #2



different zones within a week, while the variation in prices within each zone was very small. Accordingly, we model zone-level weekly retail prices. Wholesale prices at the UPC level are identical across all stores within each week.

### 3.2. Empirical Specification

As indicated previously, we approximate the reduced-form pricing equations, (3), with log-linear, linear, and polynomial models. Because the linear and polynomial models yielded empirical results that are substantively similar to the log-linear model, to conserve space we focus on the log-linear model when we describe the empirical specification in this section and the empirical results in the next section. Results of the linear and polynomial models are available from the authors on request.<sup>9</sup>

The model is specified to explain the variation in retail price of a product across 15 price zones and 52 weeks. The own wholesale price of the product, and wholesale prices of all competing products in the category, enter on the right-hand side of the equation. To control for mean differences in prices across zones, we include zone-specific intercepts. Note that demographic characteristics and competitive variables (described subsequently) vary only across zones and not across weeks; hence, their effects

<sup>7</sup> We modified Peltzman's (2000) definition to include the division by (Inventory at end of  $t$ ), which he appears to have omitted.

<sup>8</sup> Hoch et al. (1995) indicate three price zones in these data. We investigate the number of price levels by looking at the prices of several products across randomly selected weeks. Consistent with Hoch et al., we find only three levels of price in the early years of the available data (1989–1990). However, the number of price levels increases over time. By 1992, the year of our data, we begin to observe many different price levels for a product in any given week.

<sup>9</sup> Seventy-six percent of estimated own-pass-through rates from the polynomial regression are positive. Pearson correlation of these with estimated positive own-pass-through rates from the log-log model is 0.88. Correlation between the linear and log-log model estimates is 0.96. This suggests that our results are quite robust to alternative specifications of the reduced-form pricing model.

are captured by the zone-specific intercepts. The own-brand pass-through elasticity, which is the coefficient of the log of own wholesale price, is also modeled as zone specific. Cross-brand pass-through elasticities, which are the coefficients of the log of competitive wholesale prices, are assumed to be homogeneous across zones. This assumption is made primarily for parsimony. To control for the substantial variation in prices during holidays, we include in the model a holiday dummy, which takes value 1 for major holidays such as New Year, President's Day, Easter, Memorial Day, 4th of July, Labor Day, Halloween, Thanksgiving, and Christmas.

The log-linear model specification for the  $I_c$  products in category  $c$ ,  $i = 1, 2, \dots, I_c$  is as follows:

$$\ln(P_{it}^z) = \alpha_{iz} + \beta_{iz} \ln(C_{it}^z) + \sum_{j \neq i} \beta_{ij} \ln(C_{jt}^z) + \sum_{t=1}^{52} \theta_t \text{Hol}_t + \varepsilon_{it}^z, \quad (7)$$

where  $P_{it}^z$  is the retail unit price of product  $i$  in zone  $z$  in week  $t$ ,  $C_{it}^z$  is the wholesale price (cost to retailer) per unit of product  $i$  in zone  $z$  in week  $t$ ,  $\text{Hol}_t$  is a dummy indicating whether week  $t$  is a holiday week, and  $\varepsilon_{it}^z$  is a mean-zero error. The parameter  $\beta_{iz}$  is the own-brand pass-through elasticity of product  $i$  in zone  $z$ ;  $\beta_{ij}$  is the cross-brand pass-through elasticity of product  $i$  with respect to the cost of product  $j$ .<sup>10</sup>

For model estimation we consider both OLS separately by equation, and *seemingly unrelated regression* (SUR), which accommodates possible error correlations across equations within each category. In our application SUR gives virtually identical results to OLS because of the similarity of right-hand-side variables across equations,<sup>11</sup> hence we use OLS. There are approximately 780 observations (15 zones times 52 weeks, less a few zones with shorter time series) available for estimation of each equation. Our analysis of the residuals from the estimated equations indicates heteroscedasticity in several equations. Consequently we obtain heteroscedasticity-consistent asymptotic standard errors (White 1980) for robust inference.

<sup>10</sup> This model allows the pass-through *rate* to vary between holiday and nonholiday weeks. However, the estimated interaction effect is very small in all categories. We also estimated models in which the pass-through *elasticity* is allowed to depend on  $\text{Hol}$ . Here, too, the interaction effect was small, and second-stage results did not change substantively.

<sup>11</sup> The reason why SUR and OLS give virtually identical results is that the set of predictor variables for different product equations in a category is *almost* identical. The set consists of costs of all products, and holiday dummies. However, note that the cross-cost coefficients are restricted to be the same across zones while the own-cost coefficient is zone specific. Because the own-cost variable is different for different equations, this in effect implies that the set of predictor variables is different across equations.

## 4. Results

The models fit the data well. Across the 78 estimated equations, goodness of fit ( $R^2$ ) at the 50th percentile is 54%. Results are presented in the following order. First we discuss own-brand pass-through elasticities and rates. We then present an exploratory analysis of sources of variation in own-brand pass-through elasticities. This is followed by cross-brand pass-through elasticities and rates and analysis of determinants of variation in these.

### 4.1. Own-Brand Pass-Through

A total of 1,170 zone- and product-specific own brand elasticities are estimated.<sup>12</sup> These are translated into own-brand pass-through rates by multiplying the product-zone-level pass-through elasticity by the ratio of average retail price to average wholesale price. The own-brand pass-through rate is interpretable as the proportion of a unit (\$) cost change that is passed through as a change in the own-retail price. Thus, a pass-through rate of 0.50 means that a cost reduction of \$1 results in a retail price reduction of \$0.50.

Eighty-seven percent of the estimated pass-through rates are positive, and 78% of the positive rates are significantly ( $p < 0.05$ ) larger than zero. Although negative own-pass-through rates are not inconsistent theoretically,<sup>13</sup> only 5.6% of our estimates are negative and significant, some of which could be due to chance. Details of signs and significance for each category are provided in Table 3. We also show the share-weighted average, and range of own-brand pass-through rates for each of the 11 categories. Note that with the exception of toothpaste and paper towels, the category average pass-through rate is more than 0.60. Although we recognize that our results are for one particular retailer in 1992 for a few categories, it is still noteworthy that these numbers are *much closer* to the claims of retailers than to the claims of manufacturers in the Cannondale 2001 study discussed previously, but also much higher on average than retailers' claims.

There is substantial variation in pass-through rates across categories; paper towels is a relatively unresponsive category, while beer,<sup>14</sup> oat cereal, and dish

<sup>12</sup> Six of these estimated elasticities are larger than 500 in magnitude; hence, they are considered outliers and not included for further analysis.

<sup>13</sup> For a general demand function, our theoretical analysis of pricing by competing multiproduct retailers shows that own-pass-through rates need not be positive, in general. This analysis is available from the authors on request.

<sup>14</sup> The estimated own-pass-through rates for three of the six beer products are exceptionally large. These products are Budweiser 12-pack and Miller 12- and 24-packs. A possible explanation for this is the use of these products as loss leaders by the retailer. Although we were unable to access managers at Dominick's for comment, we

**Table 3** Estimated Own-Brand and Cross-Brand Pass-Through Rates

Category	Own-brand rates					Cross-brand rates		
	Number estimated	Number of negative estimates	Number of positive estimates		Mean (share weighted)	Number estimated	Number positive & significant <sup>1</sup>	Number negative & significant <sup>1</sup>
			Significantly <sup>1</sup> larger than 0	Significantly <sup>1</sup> larger than 1				
Bath tissue	90	11	73	8	0.91	30	6	13
Beer	105	0	104	46	5.58	42	13	14
Crackers	105	3	92	2	0.87	42	13	13
Dish detergent	164	25	119	21	1.11	110	21	37
Frozen OJ	75	15	52	0	0.63	20	7	6
Laundry detergent	180	4	153	25	0.83	132	39	55
Oat cereal	45	1	44	30	1.90	6	1	4
Paper towels	85	13	57	1	0.37	30	13	5
Refrigerated OJ	105	10	81	10	0.83	42	13	13
Toothpaste	150	56	69	19	0.22	90	26	32
Tuna (canned)	60	13	38	3	0.65	12	2	3
	1,164	151	882	165		556	154	195

<sup>1</sup> $p < 0.05$ .

detergent are highly responsive categories. To illustrate, we show product-level own-brand pass-through rates (average across price zones) for the laundry detergent category estimated using the pricing model in (9) (Model 1) in Table 4. Detailed product-level estimates for other categories are available from the authors on request. There is substantial variation in pass-through within the category—the largest rate (All 128) is over 21 times the smallest rate (Surf 64). Interestingly, the variation is not only across sizes of a single brand (e.g., Tide), but also occurs across brands produced by a single manufacturer. For example, Tide and Cheer, both P&G brands, have dramatically different levels of pass-through rates—Tide is very high relative to Cheer. Similarly, All and Wisk, both Unilever brands, have high pass-through rates, but another Unilever brand, Surf, receives the lowest pass-through of all 12 products. Such variation is consistent with the retail category management practice of severely discounting certain items in a category, usually “high-profile” items, and cutting back pass-through on other items to “mix-back” to the desired category profit levels (Grier 2001).

We also estimate pass-through using a simpler pricing model (Model 2 in Table 4) that omits the costs of other brands in the category. For each of the 12 products, an *F*-test rejected ( $p < 0.001$ ) the parameter restrictions inherent in Model 2 relative to Model 1. The absolute deviation between the pass-through-rate estimates from the two models is about 45% of the Model 1 estimates, varying from 0 to 340%. For some products, the pass-through rate is strongly overstated,

while for others it is biased downward due to the omission of competitive costs. One of the 12 own rates changes in sign from positive to negative when competitive costs are omitted. These differences highlight the importance of including competitive costs in the estimation of own-brand pass-through rates.

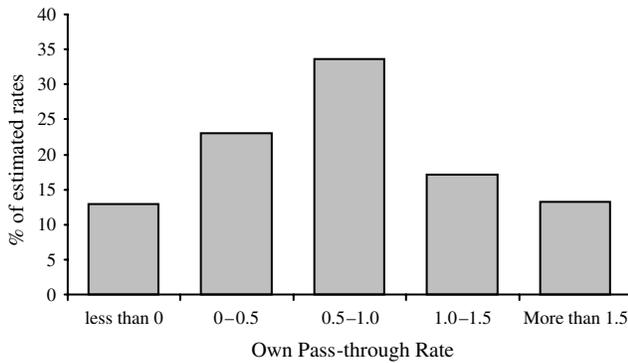
In Figure 2 we show a histogram of estimated own-brand pass-through rates. About 70% of the estimated product-zone-level pass-through rates are smaller than one, while 30% are greater than one. Approximately 14% of the estimated rates are statistically larger than one ( $p < 0.05$ ). Beer and oat cereal have an especially large fraction of rates that are bigger than one. These findings challenge the empirical generalization that “most brands receive far less than 100% pass-through” (Blattberg et al. 1995, p. G125). Other studies that have reported pass-through rates greater than one include Armstrong

**Table 4** Estimated Own-Brand Pass-Through Rates for Laundry Detergents

Products	Model 1*	Model 2*
Surf 64	0.10	−0.24
Wisk 128	0.95	0.98
Wisk 64	0.89	0.89
All 64	0.38	0.66
All 128	2.14	2.34
Cheer 64	0.39	0.39
Cheer 128	0.12	0.03
Tide 128	0.84	0.95
Tide 96	0.50	0.43
Tide 64	0.87	0.85
Tide w/bleach 128	1.15	1.07
Tide w/bleach 64	1.02	1.04

\*Model 1 includes own and competitive costs as determinants of retail price. Model 2 omits competitive costs from the pricing equations.

interviewed the beverage buyer of a large supermarket chain in the southern United States, who confirmed that these three products are commonly used by her chain as traffic generators.

**Figure 2** Histogram of Own-Pass-Through Rates

Notes. 1. Based on 1,164 estimates at the category-zone-product level.  
2. Statistical significance is shown in Table 3.

(1991), and Walters (1989). However, our finding is consistent with Tyagi's (1999, p. 512) conjecture<sup>15</sup> that "less than 100% pass-through should occur in many more settings than greater than 100% pass-through."

#### 4.2. Variation in Own-Brand Pass-Through Elasticities

We find that of the total variation in own-brand pass-through elasticities,<sup>16</sup> 75% occurs between products within categories, 23% occurs between categories, and only 2% occurs between price zones. The small variation in pass-through elasticities between zones, when combined with the finding (Hoch et al. 1995) of large variation in price elasticities of consumer demand across Dominick's stores, may be indicative of untapped profit potential for the chain through more targeted pricing.

In the following analysis<sup>17</sup> we focus on explaining the variation between products within categories, and between retail price zones. We control for between-category variation (instead of explaining it) by using category fixed effects because we have only a few categories in our data. The analysis is performed by a second-stage pooled regression of the estimated own-brand pass-through elasticities on category fixed effects, retail price zone characteristics, and variables describing products.

Previous literature (e.g., Hoch et al. 1995) has used trading-area demographic characteristics and retail

competitive variables to explain variation in price elasticities of consumer demand. The explanatory power of these variables has generally been found to be weak (see for example, Rossi and Allenby 1993), with the exception of Hoch et al., who find relatively large effects of demographic variables in cross-store data. A priori expectations of the signs of demographic coefficients are guided by the general prescription of household production theory that households with greater opportunity cost of time should be less price sensitive, although the translation of this prescription to individual variables is fraught with difficulty (see the discussion on this issue in Hoch et al. 1995). This difficulty is compounded when we seek to explain variation in retail pass-through rates, which depend not only on characteristics of consumer demand, but also on assumptions about retailer conduct. Intuitively, we expect larger demand elasticities to imply higher pass-through of trade promotions. We will interpret our estimates in the light of this expectation, but we caution that our investigation of the effects of demographic variables is best viewed as exploratory.

To explain within-category variation in own-brand pass-through, we explore the role of brand shares in category sales and in category profits. Intuitively, brand share of category sales or category profits is a measure of the importance of the item for the retailer. As discussed previously, predictions from theoretical models about the relationship between own-brand pass-through rates and market shares are mixed. Some models predict no relationship, while others predict a negative relationship. Interestingly, several empirical studies argue for a positive relationship between own-brand pass-through and brand share (e.g., Bucklin 1987, Blattberg and Neslin 1990). This idea is echoed in Curhan and Kopp (1986), who find that "manufacturer reputation" influences retailer support of trade promotions positively. Similarly, Walters (1989) found that a brand's unit-sales rank in the category was positively related to whether the retailer supported the trade promotion via pass-through. One possible reason is that larger-share brands are more likely to expand the category rather than cannibalize other brands in the category. Lal and Narasimhan (1996) explain higher pass-through for popular brands based on an inverse relationship between manufacturer and retailer margins. Intuitively as well, we expect retailers to price high-profile items competitively, leading to high pass-through rates. We model the brand share effects as category specific to allow for maximum flexibility.

We expect the retailer's pass-through to be different for store brands relative to national brands because a store brand often fulfills distinct strategic objectives

<sup>15</sup> Tyagi's prediction is based on the fact that the set of demand functional forms that imply less than 100% pass-through is quite large, whereas the set of demand functional forms that are consistent with greater than 100% pass-through is much smaller.

<sup>16</sup> The analysis reported in this section was also conducted for pass-through rates instead of elasticities. The results are not sensitive to this change.

<sup>17</sup> This analysis, and the subsequent analysis of variation in cross-pass-through elasticities, was conducted with and without the beer products, three of which were estimated to have unusually large own-pass-through rates. Substantive results were unaffected by the inclusion of beer products.

for the retailer. For example, retailers may be interested in enhancing the share of a store brand because it builds customer loyalty for the retailer (Dhar and Hoch 1997). Chintagunta (2002) finds that Dominick’s pursues dual objectives of category profit maximization and maximization of share of the store brand in the analgesics category. At the same time, manufacturers of national brands may enjoy greater market power than manufacturers of store brands (Connor and Peterson 1992), and this may be reflected in their ability to induce greater compliance in passing along trade promotions to final consumers relative to producers of private-label brands.

We specify the following model to capture the effects of demographic variables, retail store competition, brand share, and store brand effects.<sup>18</sup> Two different models are estimated—in one, brand share is operationalized as share of category sales (Model SCS), and in the other as share of category profits (Model SCP). The models are estimated based on 1,164 observations of product-zone level own-brand pass-through elasticities. To account for estimation error in the dependent variable we use weighted least squares, the weights being the inverse variance of the own-brand pass-through elasticity estimate.

$$\hat{\beta}_{iz} = \alpha + \sum_{c=1}^{C-1} \alpha_c CAT_{ic} + \delta_1 AGE60_z + \delta_2 ETHNIC_z + \delta_3 HVAL150_z + \delta_4 HSIZEAVG_z + \delta_5 JEWEL_z + \delta_6 EDLP_z + \gamma_1 STORE_i + \sum_{c=1}^C \gamma_{2c} SHARE_{ic} + \varepsilon_{iz}, \quad (8)$$

where  $\hat{\beta}_{iz}$  is the estimated own-brand pass-through elasticity of product  $i$  in price zone  $z$ . The variable  $CAT_{ic}$  is a dummy variable indicating whether a product  $i$  is in category  $c$ ,  $EDUC_z$ ,  $AGE60_z$ ,  $ETHNIC_z$ ,  $HVAL150_z$ ,  $SHOPINDX_z$ ,  $JEWEL_z$  is the average distance in miles to the nearest Jewel store (high-low competitor) from stores in price zone  $z$ ,  $EDLP_z$  is the average distance in miles to the nearest Cub Foods or Omni store (EDLP competitor) from stores in price zone  $z$ ,  $STORE_i$  indicates whether product  $i$  is a store brand, and  $SHARE_{ic}$  is the share of brand  $i$  in category  $c$  unit sales, or share of category  $c$  profits. We also include the following demographic characteristics of the trading areas of stores in price zone  $z$ . The variable  $AGE60$  is the % over

age 60,  $ETHNIC$  is the % African-American or Hispanic,  $HVAL150$  is the % with home value greater than \$150,000, and  $HSIZEAVG$  is the average size of the household.

In Table 5 we show weighted least squares estimates of the parameters from both models. In the SCS model, all four of the demographic effects are found to be significant. We find that older population, bigger ethnic population, higher home values, and larger household size, are positively related to larger pass-through rates. The sign of the home-value variable is contrary to expectation based on demand elasticities. One possible explanation is the omission of Income from the model, which was found to have mixed signs by Hoch et al. (1995, p. 24) but is highly correlated with Home Value. The two store competition variables—distance to Jewel, and distance to EDLP—are not significant, consistent with Hoch et al. (1995), who also found that trading-area competitive variables provide poor explanatory power for variation in price sensitivities. In the SCP model, none of the demographic variables are found to be significant, which is due to high collinearity between the share of category profits variables and the demographic variables.

In both SCS and SCP models we find that store brands receive significantly smaller pass-through than

**Table 5** Determinants of Own-Brand Pass-Through Elasticities

Parameter	Weighted least squares estimates ( <i>t</i> -values)	
	Shares of category sales as predictors (share = SCS)	Shares of category profits as predictors (share = SCP)
AGE60	<b>0.95 (2.68)</b>	0.22 (0.63)
ETHNIC	<b>0.38 (2.25)</b>	0.13 (0.80)
HVAL150	<b>0.45 (3.28)</b>	0.13 (0.94)
HSIZEAVG	<b>0.35 (2.39)</b>	−0.06 (−0.41)
JEWEL	−0.00 (−0.22)	0.03 (1.21)
EDLP	0.01 (1.21)	0.00 (0.10)
Store brand dummy	<b>−0.07 (−1.74)</b>	<b>−0.18 (−4.64)</b>
<i>Effect of brand shares</i>		
Bath tissue	<b>7.09 (14.89)</b>	<b>6.75 (14.70)</b>
Beer	−0.48 (−1.51)	−0.33 (−0.95)
Crackers	<b>1.70 (2.56)</b>	<b>1.56 (2.47)</b>
Dish detergent	<b>9.83 (8.92)</b>	<b>2.23 (1.65)</b>
Frozen orange juice	−0.80 (−1.00)	−0.24 (−0.32)
Laundry detergent	<b>2.46 (4.78)</b>	<b>7.19 (11.77)</b>
Oat cereal	<b>2.10 (2.62)</b>	<b>1.54 (2.52)</b>
Paper towels	<b>2.48 (2.50)</b>	<b>1.52 (2.01)</b>
Refrigerated orange juice	<b>4.93 (6.24)</b>	<b>5.30 (5.81)</b>
Toothpaste	−1.94 (−1.96)	−1.02 (−1.01)
Tuna (canned)	<b>2.71 (2.78)</b>	<b>−2.30 (−5.61)</b>
$R^2$	0.47	0.49

Note.  $N = 1,164$ , significant ( $p < 0.10$ ) effects are in bold. Category-specific fixed effects are not shown.

<sup>18</sup> A possible concern with our results is that the included demographic variables do not sufficiently control for demand differences between products and categories. To assess the robustness of our results, we also included in the second-stage regressions (Equation (8) below), product-zone-specific own-price demand elasticities based on homogeneous logit models. The substantive results remained unchanged and the coefficient of the demand elasticity was not statistically significant.

national brands. This is an important finding in light of the *belief* that store brands always get 100% pass-through (e.g., Hoch 1996). One possible explanation for this finding is that national brand manufacturers have greater bargaining power over retailers than do private-label manufacturers, a hypothesis that is supported in studies that find that retail margins of national brands are lower than margins for private-label brands. (See Barsky et al. 2003 for such evidence from the Dominick's data, and Ailawadi and Harlam 2004 for evidence from other retail chains.) Our evidence on pass-through rates provides additional support for the hypothesis that manufacturers of national brands enjoy greater bargaining power over retailers than manufacturers of private-label products.

The effect of brand share of unit sales is significantly different from zero for nine of the eleven categories ( $p < 0.05$ ) in the SCS model. The effect is negative in only one of these nine categories—toothpaste. In the SCP model, eight of the eleven category-specific effects are significant, and one of these—tuna—is negative. In general, these results support the view that larger brands and more profitable brands receive greater pass-through. This asymmetry could reflect differences in manufacturers' bargaining power. Alternatively, it could reflect differences in menu costs of retail price changes (e.g., Dutta et al. 1999). Because part of the cost of price changes is fixed, retailers may be more reluctant to pass on changes in wholesale prices of small-share brands than of large-share brands. Our finding is consistent with previous empirical studies discussed above (e.g., Walters 1989, Curhan and Kopp 1986).

#### 4.3. Cross-Brand Pass-Through

In each of the 11 categories we estimate  $n * (n - 1)$  cross-brand pass-through elasticities, where  $n$  is the number of products in the category. Denote the cross-brand pass-through elasticity of retail price of product  $i$  to changes in wholesale price of product  $j$  as  $\beta_{ij}$ . Since  $\beta_{ij} = (\partial p_i / \partial w_j) * (w_j / p_i)$ , we transform the estimated cross elasticity to a cross-brand pass-through rate by multiplying by the ratio of average retail price of product  $i$  to average wholesale price of product  $j$ . The cross-brand pass-through rate is interpreted as the proportion of a change in wholesale price of product  $j$  that is passed through to the retail price of product  $i$ . Recall that positive cross-brand pass-through implies that trade promotions on brand  $j$  lead to retail price reductions of brand  $i$ , while negative cross-brand pass-through implies that trade promotions on brand  $j$  lead to price increases on brand  $i$ . We refer to  $i$  as the target brand, and  $j$  as the trade-promoted brand. Positive cross-brand pass-through may reflect the retailer's attempt to guard business on the target brand, while negative cross-brand pass-through may

be interpreted as an attempt to drive consumers from the target brand to the trade-promoted brand.

In Table 3 we show details of signs and significance of cross-brand pass-through rates for each category. In total, we obtain 556 cross-brand pass-through rates. Of these, 349 (approximately 63%) are significantly different from zero ( $p < 0.05$ ). In each category, significant cross-brand pass-through rates have a mix of positive and negative signs. Across the 11 categories, 154 (27.7%) cross-brand pass-through rates are positive and 195 (35.1%) are negative.

In a general setting with differentiated products and static multiproduct pricing, theory implies a wide range of possible cross-brand pass-through rates, including positive and negative signs. Only after imposing specific supply, demand, or behavioral restrictions can we predict cross-brand pass-through rates with a specific sign. For instance, the vertical Nash equilibrium model predicts zero cross-brand pass-through. A homogeneous logit demand system with a category manager yields strictly negative cross-brand pass-through. By contrast, if the retailer acts as a brand manager, cross-brand pass-through is strictly positive.

#### 4.4. Variation in Cross-Brand Pass-Through Elasticities

We consider the role of brand shares in category unit sales, and brand shares in category profits, in explaining cross-brand pass-through rates.<sup>19</sup> Intuitively, we consider the shares to be measures of the relative importance of the two brands in the relevant pair. Theoretical models provide mixed predictions on the role of market shares. Some models imply no dependence between cross-brand pass-through elasticities and market shares of either  $i$  or  $j$  (e.g., linear demand), others imply a positive relationship, and yet others imply a negative relationship. Because we expect strategic retailer behavior with respect to the store brand, we also consider whether each product is a store brand or national brand.<sup>20</sup>

We explore these relationships by conducting a second-stage exploratory analysis to discriminate between positive and negative elasticities. We include the following variables as determinants of the sign of the cross-brand pass-through elasticity:  $RELSHARE_{ji}$ , which is the ratio of share of the promoting brand  $j$  to share of the target brand  $i$ ;  $STORE_j$ , a dummy variable indicating whether or not the promoting brand  $j$

<sup>19</sup> We also analyzed variation in cross-pass-through rates instead of elasticities and arrived at similar conclusions as reported here.

<sup>20</sup> We also expect cross pass-through to be related to demand parameters such as cross price elasticities. However, since we do not estimate demand models we are unable to explore this relationship directly. This is a drawback of our reduced form approach.

is a store brand; and  $STORE_i$ , a dummy variable indicating whether or not the target brand  $i$  is a store brand.

Two separate models are estimated: one with the variable  $RELSHARE_{ji}$  computed based on share of category sales and the other computed based on share of category profits. We develop the following logit model to discriminate between positive and negative cross-brand pass-through and estimate it using the 556 observations of cross-brand pass-through elasticities.

$$\begin{aligned} \text{Log-Odds of } (Z_{ijc} = 1) \\ = \lambda + \sum_{c=1}^{C-1} \delta_c CAT_{ijc} + \theta_1 RELSHARE_{ji} \\ + \theta_2 STORE_j + \theta_3 STORE_i, \end{aligned} \quad (9)$$

where  $Z_{ijc} = 1$  indicates that  $\hat{\beta}_{ij}$  for product pair  $ij$ , in category  $c$ , is positive, zero otherwise; and  $CAT_{ijc}$  is one if product pair  $ij$  is in category  $c$ , zero otherwise.

Selected maximum-likelihood estimates are shown in Table 6. Results from the two models based on share of category sales and share of category profits are consistent. The negative coefficient of  $RELSHARE_{ji}$  indicates that when the trade-promoted brand is large, cross-brand pass-through is less likely to be positive. In other words, trade promotions on large brands are unlikely to induce the retailer to reduce retail prices of competing smaller share brands in the category. On the other hand, trade promotions on smaller brands induce the retailer to reduce retail prices of larger competing brands in the category.

These results, combined with our earlier finding on own-brand pass-through, imply that manufacturers of small-share brands suffer a triple whammy: Their trade promotions not only receive lower pass-through to the retail price, they also encourage the retailer to reduce prices of competing brands, thereby diluting the impact of their retail price reductions. Furthermore, when larger-share brands are trade promoted, the small-share brand's retail price is not likely to be reduced.

The store brand parameter is negative for the target brand and positive for the trade-promoted brand

**Table 6** Determinants of Positive Relative to Negative Cross-Brand Pass-Through Elasticities

Maximum Likelihood Estimates and ( <i>t</i> -values) from Logit Model		
Variable	Shares of unit sales as predictors	Shares of category profits as predictors
$RELSHARE_{ji}$	<b>-0.23</b> (97.86)	<b>-0.42</b> (190.20)
$STORE_i$	<b>-0.20</b> (16.42)	<b>-0.22</b> (16.91)
$STORE_j$	<b>0.69</b> (83.81)	<b>0.64</b> (77.97)

Note.  $N = 556$ , significant effect ( $p < 0.05$ ) are in bold. Category-specific fixed effects are not shown.

in both models. Examining the four combinations of the two dummy-variable coefficients, we find that the highest probability of positive cross-brand pass-through occurs when the promoting brand is a store brand and the target brand is a national brand, and the lowest probability occurs when the promoting brand is a national brand and the target brand is a store brand. This indicates that wholesale price reductions on national brands are less likely to induce the retailer to reduce retail prices of store brands than the other way around. Thus, a producer of a national brand is less likely than a private-label producer to find that the retailer has diluted the impact of the reduction in its wholesale price by reducing the retail price on a competing brand.<sup>21</sup> This provides further support for the hypothesis that manufacturers of national brands hold greater sway over retailers' pricing policies than do manufacturers of store brands.<sup>22</sup>

## 5. Conclusions

We provide a comprehensive description of a large supermarket's pass-through behavior across 78 products in 11 large categories. Our findings suggest that pass-through varies substantially across products and across categories. Own-brand pass-through rates are, on average, higher than 0.60 for most categories, a finding that is at odds with the claims of manufacturers about retailers in general. Importantly, we find evidence of significant positive and negative cross-brand pass-through effects, indicating that prices of competing products are adjusted upward or downward in response to a change in the wholesale price of any particular product. Our pooled analysis across categories of own-brand and cross-brand pass-through rates reveals important asymmetries in retailer pass-through response on large versus small brands, and on national brands versus private labels. These findings provide insights into the nature of competition between manufacturers.

By describing and characterizing pass-through across a large number of brands and categories, we hope to provide the impetus for development of more general theoretical models of retail pass-through. In addition to serving a descriptive purpose, our estimates could be used for normative purposes. Retailers' pass-through is a critical determinant of manufacturer profitability of trade deals. Silva-Risso et al. (1999) show that accurate estimates

<sup>21</sup> This result is not inconsistent with the retail practice of "shielding," where a store brand is displayed, often at regular price, next to a deeply discounted national brand to encourage price comparisons between the national brand and store brand.

<sup>22</sup> These conclusions are entirely robust to the inclusion of average logit demand elasticities of both products  $i$  and  $j$  in the second-stage regression.

of pass-through are critical for manufacturers' trade-promotion planning.

We believe an important area for future research is to examine the determinants of differences in retail pass-through across categories. The brand-switching fraction of sales increases induced by consumer promotions has been found to vary strongly across categories (Van Heerde et al. 2003). Bell et al. (1999) find that differences in the elasticities of consumer response to price promotions are explained by category characteristics such as storability, size of assortments, perceived differentiation, etc. A similar examination of retail pass-through rates should yield insights into cross-category differences in overall effectiveness of manufacturer promotions, taking into account the mediating role of the channel. In light of our finding of a positive relationship between retail own-brand pass-through and market share, it would be useful to examine the relationship between different components of consumer response to promotions and market shares of brands.

Finally, we recognize some limitations of our work. Our model of retail pricing does not explicitly consider the role of retail competition. This is primarily because our data are for a single chain. Further, our assumption is consistent with many other studies such as Besanko et al. (1998) and Sudhir (2001), who also assume that the retailer prices individual categories as a monopolist. Our second-stage analysis of own-brand pass-through included competitive variables such as distance to the nearest competitor. However, consistent with most previous work, these variables were not found to have a significant impact on pass-through. Future work should include categories such as beverages, whose role as a loss-leader category is then anticipated in the model specification.

To investigate the robustness of the log-linear specification of the reduced-form pricing equations, we estimate two other models—linear and polynomial. These models yield results that are substantively similar to findings from the log-linear model. However, future research could investigate the potential benefits of an even more flexible specification. For instance, a semiparametric specification could allow for a more flexible treatment of the cross-cost effects and the demographic effects.

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