Published online ahead of print July 23, 2009

MARKETING SCIENCE
Articles in Advance, pp. 1–18
ISSN 0732-2399 | EISSN 1526-548X

DOI 10.1287/mksc.1090.0509

Channel Pass-Through of Trade Promotions

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Packaged goods manufacturers spend in excess of $75 billion annually on trade promotions, even though their effectiveness has been hotly debated by academics and practitioners for decades. One reason for this ongoing debate is that empirical research has been limited mostly to case studies, managerial surveys, and data from one or two supermarket chains in a single market. In this paper, we assemble a unique data set containing information on prices, quantities, and promotions throughout the entire channel in a category. Our study extends the empirical literature on pass-through in three important ways. First, we investigate how pass-through varies across more than 1,000 retailers in over 30 states. Second, we study pass-through at multiple levels of the distribution channel. Third, we show how the use of accounting metrics, such as average acquisition cost, rather than transaction cost, yields biased estimates of pass-through and therefore overstates the effectiveness of trade promotions.

We find that mean pass-through elasticities are 0.71, 0.59, and 0.41, for the wholesaler, retailer, and total channel, respectively. More importantly, at each level of the channel we observe large variances in pass-through estimates that we explain using various measures of cost and competition. Surprisingly, we find that market structure and competition have a relatively small impact on pass-through.

We conclude by showing how the profitability of manufacturer and wholesaler deals can be improved by utilizing detailed effectiveness estimates. For example, a manufacturer using an *inclusive* trade promotion strategy might offer a 10% off invoice deal to all retailers on every product. This strategy would decrease manufacturer and wholesaler profits for 56% of product/store combinations, whereas retailers experience a profit boost in 96% of cases. Manufacturers and wholesalers can avoid unprofitable trade deals for specific products and retailers by utilizing estimates of pass-through, consumer price elasticity, and margins. Compared to the inclusive strategy, such a *selective* trade promotion strategy would improve deal profitability by 80% and reduce costs by 40%.

Key words: trade promotion; pass-through; channels; competition; measurement
History: Received: November 26, 2007; accepted: March 28, 2009; processed by Michel Wedel. Published online in *Articles in Advance*.

1. Introduction

Blattberg and Neslin (1990) define manufacturer trade promotions as special incentives directed toward other members of the distribution channel. Consumer packaged goods industry reports show that trade promotion spending exceeds $75 billion annually and accounts for over 60% of manufacturers' marketing budgets (Cannondale 2001). In nonvertically integrated channels, manufacturers rely on trade promotions to influence retailer and wholesaler prices, and thus consumer demand. However, their effectiveness at lowering end-user price has been hotly debated by managers. Some manufacturers accuse retailers of pocketing a large fraction of trade dollars to enhance their bottom line. In contrast, retailers claim that the majority of trade dollars is passed through to consumers (Cannondale 2001).

The reason the debate between retailers and manufacturers has raged on for decades may in part be explained by the scant empirical research on channel pass-through. Chevalier and Curhan (1976) conducted one of the first studies on channel pass-through but referred to their 24-week study of one supermarket as a case study. Subsequent empirical studies on pass-through have also been limited to one or two supermarket chains (Curhan and Kopp 1987, Walters 1989, Meza and Sudhir 2006, Dubé and Gupta 2008, Ailawadi and Harlam 2009). Besanko et al. (2005) (henceforth BDG) studied 11 different product categories and 78 products in an extensive analysis of pass-through by a supermarket chain in a single geographic market. A limitation of single-market data is that it can be difficult to accurately measure how local market characteristics, such as income, affect pass-through.

For this paper we assembled a unique data set allowing us to contribute to the pass-through literature in three important ways. First, our data set spans thousands of retail outlets located in over 30 different states, providing an opportunity to assess how relative competitive position and market structure affect pass-through. For example, Bronnenberg et al. (2007) document that brand shares for ground coffee and mayonnaise differ substantially by geographic region.

The second contribution is readily apparent from the title: channel pass-through. Whereas previous studies focused solely on the end of the distribution channel, we obtained information on all financial flows throughout the entire channel for over 100 products in a major consumer packaged goods category. The structure of the vertical channel—which includes manufacturer, wholesaler, and retailer—enables us to quantify the effect of upstream channel intermediaries on pass-through.

Third, our data allow us to address how different cost measures influence pass-through estimates. Four recent econometric studies on pass-through rely on accounting measures provided by Dominick's Finer Foods (BDG, Meza and Sudhir 2006, Pauwels 2007, Dubé and Gupta 2008). These authors recognize accounting costs as "a limitation to be lived with when measuring pass-through" (Meza and Sudhir 2006, p. 354) as they do not represent true economic marginal cost. Our data contain measures of all financial and product flows in the channel, including economic marginal cost (i.e., transaction cost).

We demonstrate how manufacturers can use estimates of pass-through, price elasticity, and margins to improve trade promotion profitability. To help manufacturers scrutinize unprofitable trade deals, we investigate whether they result from demand conditions (i.e., price inelastic demand) or strategic retail behavior (i.e., pocketing trade dollars). A trade deal strategy focused on avoiding wasteful trade expenditures could have a significant impact at each channel level. Our study provides valuable insights into two alternative strategies' relative costs and benefits to manufacturers, wholesalers, and retailers and identifies various important questions for future research.

A recent paper in this domain by Ailawadi and Harlam (2009) uses cost and promotion data to calculate the ratio of promotional inputs and outputs by retailers in one chain. Although these authors neither address pass-through throughout the entire channel nor the profitability implications of trade deals, they do provide important insights into the annual impact of manufacturer-level trade spending in various forms (e.g., lump-sum payments, market development funds, etc.).

The remainder of this paper is organized as follows: In §2 we develop predictions on pass-through and investigate the forces influencing pass-through across products, retailers, wholesalers, and geographic regions. Section 3 lays out the methodology. We describe our data in §4 and report the results in §5. Finally, §6 provides managerial implications, and §7 contains conclusions and directions for future research.

2. Predictions on Pass-Through and Its Moderators

In a recent article BDG argue that the extant literature does not provide a clear and consistent set of predictions on vertical channel pass-through. They posit that the degree of pass-through obtained from analytical models is determined by assumptions about the nature of the demand curve. We formalize their argument below. Assume a channel member faces a marginal cost of goods c. The profit-maximizing price must satisfy

$$p = \frac{\eta c}{1+\eta}, \tag{1}$$

where $\eta = q'(p/q)$, which is the price elasticity of demand. It is important to recognize that η is a function of own price, competitors' prices, and other parameters. We are interested in the pass-through elasticity, which equals $\beta = (dp/dc)(c/p)$. Noting that η is implicitly a function of c, we have

$$\frac{dp}{dc} = \frac{\eta}{1+\eta}\left(1 - \frac{d\eta/dp}{(1+\eta)^2}(c)\right)^{-1}. \tag{2}$$

Letting $\eta_p = d\eta/dp$, we have

$$\beta = \frac{(1+\eta)^2}{(1+\eta)^2 - c\eta_p}. \tag{3}$$

Equation (3) demonstrates that analytic models may generate different predictions on pass-through. For constant price elasticity models (e.g., log-log demand), $\eta_p = 0$ and the pass-through elasticity equals 1. For linear demand models, $\eta_p < 0$ and pass-through elasticity is less than 1. Finally, if demand is sufficiently convex, then $\eta_p > 0$ and the pass-through elasticity is greater than 1. In sum, predictions on the level of pass-through elasticity depend on the demand function. Tyagi (1999) characterizes related results for the pass-through rate, which equals dp/dc.

Comparative statics also depend on the shape of the demand curve. For example, as competition increases, price approaches marginal cost and pass-through elasticity approaches 1. If $\beta < 1$, increased competition leads to an increase in pass-through elasticity; if $\beta > 1$, increased competition leads to a decrease in pass-through elasticity.

We conclude that the magnitude of the pass-through elasticity depends on η_p. Similarly, comparative statics on the pass-through elasticity may also depend on η_p. Whereas analytical models in marketing yield few testable hypotheses, other research suggests two moderators of pass-through, cost of channel flows and competition, which we discuss next.

2.1. Cost of Channel Flows

Intermediaries who perform channel flows expect to be compensated for their costly efforts (Coughlan et al. 2006). Passing through fewer trade dollars is one way to obtain compensation. A survey by Nielsen confirms such behavior occurs in practice (Wellam 1998). Although retailers report that approximately 15% of trade deals goes directly to their bottom line, manufacturers believe this number is upward of 30%. In fact, some industry experts claim retailers would not break even without trade deals.

The costs of changing prices may partially explain pocketing of trade deals by retailers. Menu, managerial, and customer costs have been identified as sources of price rigidity and low pass-through of cost shocks (e.g., Zbaracki et al. 2004). Kim and Staelin (1999) develop an analytical model in which manufacturers use trade deals even though they are aware retailers will pocket a portion of the money. In their model, retailers use deals to either offer price promotions to consumers or provide nonmonetary forms of promotional support (e.g., feature or display).[1] However, the authors do not address which alternative channel flows might be supported with the pocketed trade dollars.

Whereas the link between price rigidity and the costs of changing prices has received recent attention in marketing (e.g., Srinivasan et al. 2008) and economics (e.g., Zbaracki et al. 2004), the implications of costs of channel flows on pass-through have not. A notable exception is Arcelus and Srinivasan (2006), who developed an analytical model of the role of inventory holding costs on pass-through. The impact of cross-sectional differences in marginal costs has been studied in the literature on pass-through of exchange-rate fluctuations (e.g., Goldberg and Verboven 2001, Corsetti and Dedola 2005). The general finding is that local costs limit the pass-through of changes in exchange rates. Accordingly, we expect channel flow costs to diminish the level of trade deal pass-through.

Willingness to provide small shipments to retailers is an important component of a wholesaler's delivery service. Although fill-in deliveries reduce the likelihood of stock-outs and ensure the availability of a more complete assortment, they significantly increase wholesaler costs. To compensate, a wholesaler may pocket a greater fraction of trade deals. A similar argument could be made for a wholesaler serving a large geographical area. The greater the distance covered to deliver the product, the higher the cost to the wholesaler and the lower the expected level of pass-through. In concentrated retail markets, logistical efficiencies may lower wholesaler costs and increase pass-through.

When products have been delivered to the retailer, additional work may be required before the product can be put on store shelves. Bulk-breaking is a common task retailers perform. Consider a product shipped by the wholesaler in a container of 20 units that is unpacked by the retailer into 20 separate items. To cover these costs we expect lower retailer pass-through on products that require bulk-breaking.

2.2. Competition

A well-known result from vertical channel theory is the positive relationship between retail competition and pass-through (Heflebower 1957). The lack of competition may enable retailers to pocket trade promotions and reduce pass-through. Competition can be increased by moving from exclusive to intensive distribution, which diminishes individual retailers' market power. In the limit of perfect retail competition, retail price equals wholesale cost and pass-through is 100%. Although empirical evidence to support this prediction is limited, our multimarket data afford a direct test.

Channel members are more likely to pass-through trade deals when demand is elastic (Tyagi 1999). When lower prices result in substantial demand increases, passing through 100% or greater may be profitable. However, if an intermediary anticipates little impact on demand, pocketing the trade deal could be the most profitable option. Pass-through should also depend on the cross-price elasticities of demand in a category (Moorthy 2005). A retailer's performance is more strongly linked to the overall demand

[1] In this paper we focus on monetary pass-through and control for feature and display support provided by the retailer (see §3).

in a category than to the sales of a single brand (Nijs et al. 2001). Thus, when a brand with elastic demand is able to expand the category rather than steal sales from competitors, it likely receives higher pass-through.

Power—a concept often studied in the marketing channels literature—and competition are directly linked. El-Ansary and Stern (1972, p. 47) define power as the ability of one channel member "to control the decision variables in the marketing strategy of another channel member at a different level in the channel." In this study we focus on the ability to influence prices charged at a lower level of the channel. A powerful wholesaler can influence the price charged to the consumer by a retailer. Similarly, a wholesaler's (retailer's) ability to withstand the influence of the manufacturer (wholesaler) in setting prices is a reflection of countervailing power (Gaski 1984).

Emerson (1962) argued that dependence is a key determinant of channel power. If competition increases at one channel level, channel members at another level will have more power, will have more alternative sources of utility, and will face less dependence. For example, in a competitive retail market wholesalers will have more alternatives to get products to market, swinging the balance of power away from the retailer.

We expect manufacturers to have more influence over less powerful wholesalers and less influence over more powerful wholesalers. Therefore, less powerful wholesalers should be more inclined to pass-through trade deals in the channel. Similarly, powerful retailers may be better able to withstand wholesaler pressure to pass-through trade deals. Although they may "pull" trade deals through the channel—leading to more pass-through by the wholesaler—we expect them to act opportunistically and pocket a larger proportion of the trade deals offered.

Moreover, the power or standing of a product could also influence the level of pass-through observed in the market. Empirical evidence indicates that pass-through rates depend on a product's market share, which is a common measure of market power (Chevalier and Curhan 1976). Ailawadi and Harlam (2009) find that larger manufacturers achieve higher levels of pass-through. Similarly, according to Walters (1989) a brand's unit-sales rank in the category is positively related to retailer support of trade promotions. Both analytical models (e.g., Lal and Narasimhan 1996) and empirical evidence (Chevalier and Curhan 1976, Walters 1989, Pauwels 2007) indicate that retailers are inclined to promote leading brands to expand the category (Bronnenberg and Mahajan 2001) and increase store traffic (Moorthy 2005). Leading brands enjoy high levels of consumer awareness and familiarity (Keller 1993) and have a large customer base that will be affected by a retail-price change. Because promotions for leading brands offer enhanced benefits, we expect more retailer pass-through of trade deals.

2.3. Reconciling Predictions

In this section's introduction we argued that predictions from analytic models depend on assumptions the researcher is willing to make on the nature of demand. For $\eta_p \leq 0$, analytic models yield the same predictions on both cost and competition as discussed in §§2.1 and 2.2, respectively. We interpret our empirical findings in §5 in light of these conditional predictions; supported by the ubiquitous use of log-log and linear demand models in the marketing literature, we assume $\eta_p \leq 0$.

In the next section we describe the methodology used to quantify wholesaler and retailer pass-through of trade deals and link variability in trade deal effectiveness to various measures of competition and cost. We define these metrics in §4 and discuss the findings in §5.

3. Methodology

As in BDG, we use a log-log specification to estimate pass-through elasticities.[2] Our data contain price and cost time series for thousands of retailers and products at two channel levels: wholesaler to retailer (W to R) and retailer to consumer (R to C). We estimate pass-through using the following two equations:

$$\log P^r_{wrpt} = \alpha^r_{wrp} + \beta^r_{wrp} \log P^w_{wrpt} + \epsilon^r_{wrpt}, \tag{4}$$

$$\log P^c_{wrpt} = \alpha^c_{wrp} + \beta^c_{wrp} \log P^r_{wrpt} + \lambda_{wrp} F\&D_{apt} + \gamma_{wrp} F\&D_{apt} \times P^r_{wrpt} + \epsilon^c_{wrpt}, \tag{5}$$

where P^r_{wrpt} is the price charged to retailer r by wholesaler w for product p in week t. P^w_{wrpt} is the price offered by the manufacturer to the wholesaler on product p for sale to retailer r at time t, and P^c is the price charged to the consumer by the retailer.[3]

[2] BDG considered alternative model specifications but did not find any substantive differences in their estimates.

[3] Simultaneous estimation of Equations (4) and (5) would require weekly observations at both the W-to-R and the R-to-C levels. However, when consumer sales or wholesaler shipments do not occur, price and cost information are not recorded. Consequently, that week's data cannot be used in estimation, a limitation shared with BDG, Dubé and Gupta (2008), and the majority of studies using store-level scanner data. In our application simultaneous estimation would result in a loss of 14% of all observations. Because a disproportionate number of observations is missing for low-volume products with infrequent shipments and fewer weeks of nonzero sales, parameter bias is induced. The correlation of the residuals from the separately estimated equations is limited (−0.06). Simultaneous estimation results are not reported because of space constraints but are available from the first author on request.

We also include feature and display activity (F&D) for retail-trade account a and a mean-centered interaction between price and F&D in the R-to-C model. These variables control for changes in price and pass-through linked to F&D support provided by the retailer for a product. Finally, we account for seasonal variation as well as store and product-specific fixed effects in both models.

To investigate cross-sectional variation in pass-through, we formulate a hierarchical Bayesian model to link the β estimates to a series of moderators. The model's first stage is given by Equations (4) and (5). The second stage is formulated as follows:

$$\theta_{wrp} \mid \Delta, \Omega, Z_{wrp} \sim \mathrm{N}(\Delta Z_{wrp}, \Omega), \tag{6}$$

where θ_{wrp} is the vector of parameters in Equations (4) and (5), and Z_{wrp} are measures of cost and competition discussed in §2. The coefficients in Δ measure the impact on pass-through of the moderators in Z_{wrp}. Measurement of the covariates in Z_{wrp} is discussed in §4. We assume the following first-stage error structure for both pass-through equations:

$$\epsilon_{wrpt} \mid \sigma \sim \mathrm{N}(0, \sigma^2_{wrp}), \tag{7}$$

and specify the hierarchy for σ_{wrp} as

$$\log(\sigma_{wrp}) \mid \sigma_\mu, \sigma_\sigma \sim \mathrm{N}(\sigma_\mu, \sigma^2_\sigma), \tag{8}$$

using a log transformation to ensure supported values are strictly positive. Estimation details and prior specification for the linear hierarchical Bayesian model are provided in Appendix A.

4. Data

We assembled a data set that contains information on shipments and financial flows throughout the distribution channel for a large number of products in a major consumer packaged goods category. We observe weekly shipments to and prices paid by wholesalers and retailers. Each outlet is served by one wholesaler.

Wholesalers set the price paid by retailers for each product. Manufacturers provide wholesaler incentives to lower prices using a mechanism analogous to retail scan-backs (Drèze and Bell 2003). In a retail scan-back, transactions are audited and the retailer is reimbursed for every unit sold at a promotional price. In our setting the manufacturer audits weekly prices paid by retailers. If a wholesaler offers the retailer a price below a prespecified level, the manufacturer will (partially) reimburse the wholesaler when a trade deal is in effect. Our measure of wholesaler cost is the manufacturer price minus any promotional reimbursements offered. Note that realized and offered promotional reimbursements may differ as the former depend on the price wholesalers charge retailers.[4]

Nielsen provided data for over 1,000 grocery and drug stores in more than 30 states. For every product in the category, we have two years of data on prices charged and quantities sold to the consumer. Moreover, because information is available for all outlets selling the products studied, we are able to assess local retail competition.[5] We have upstream channel information for over 30 brands sold in a variety of package sizes and forms.

Choosing an appropriate cost metric for wholesaler and retailer is key in calculating pass-through. As stated earlier, the accurate information on all financial flows in the channel is a unique feature of our data. The cost measures used in our analyses are the price offered to the wholesaler at time t for the W-to-R model and the price charged to the retailer at time t for the R-to-C model. A limitation of using these transaction costs is missing data in weeks without shipments or sales. We therefore focus on those weeks in which they do occur (see also BDG) and provide a conceptual and quantitative assessment of cost metrics in §5.2.

To estimate pass-through, we use three price series: price offered to the wholesaler (P^w), price charged to the retailer (P^r), and price paid by the consumer (P^c). Descriptive statistics are provided in Table 1.

Figure 1 shows two examples of the data used to estimate pass-through. Panel A demonstrates near-perfect trade deal pass-through at each channel level; the wholesaler lowers the price to the retailer when offered a lower price by the manufacturer. The retailer, in turn, provides a discount to consumers when offered a trade deal. Panel B shows a setting in which manufacturer and wholesaler discounts rarely lead to a consumer price promotion. In our analysis we seek to both measure pass-through and explain its variation. In the remainder of this section we describe the set of covariates used to explain variability in pass-through across wholesalers, retailers, products, and geographies.

4.1. Covariates in Z

We use measures of channel flow costs and competition as well as several control variables to explain cross-sectional variation in pass-through. Covariate descriptions and summary statistics are provided in Tables 2 and 3.

4.1.1. Cost of Channel Flows. Costs of channel flows are captured by *service level*, *distribution of sales*, *distance to the retailer*, and *bulk-breaking*. We define

[4] Manufacturers using scan-backs reimburse up to $\$X$ for each unit a wholesaler sells to a retailer at a discount.

[5] Consumer sales data are not available for every outlet.

Table 1 **Descriptive Statistics on Price to Wholesaler (P^w), Retailer (P^r), and Consumer (P^c)**

	W-to-R model		R-to-C model	
Statistic	P^w	P^r	P^r	P^c
Mean	1.00	1.00	1.00	1.00
Minimum	0.48	0.57	0.57	0.54
10th percentile	0.68	0.74	0.74	0.72
25th percentile	0.81	0.84	0.84	0.85
Median	1.06	1.04	1.05	1.02
75th percentile	1.15	1.12	1.12	1.14
90th percentile	1.21	1.20	1.20	1.23
Maximum	1.92	1.84	1.84	2.06
Total observations	1,418,405		1,338,425	
Average observations	61		58	

Notes. Mean prices are indexed for confidentiality reasons. The total number of time-series observations is counted across all wholesalers, retailers, and UPCs. The average number of time-series observations is counted per wholesaler, retailer, and UPC.

service level as the percentage of wholesaler shipments that consists of fewer than five units. Each unit may contain multiple items (see also the discussion on bulk-breaking below). For example, a wholesaler may deliver two units of product A and one unit of product B in a three-unit shipment. Although small shipments allow retailers to fill in store shelves, they constitute an extra cost for the wholesaler. For an average wholesaler, approximately 24% of shipments are less than five units.

Figure 1 **Examples of the Data Series Used to Estimate Pass-Through**

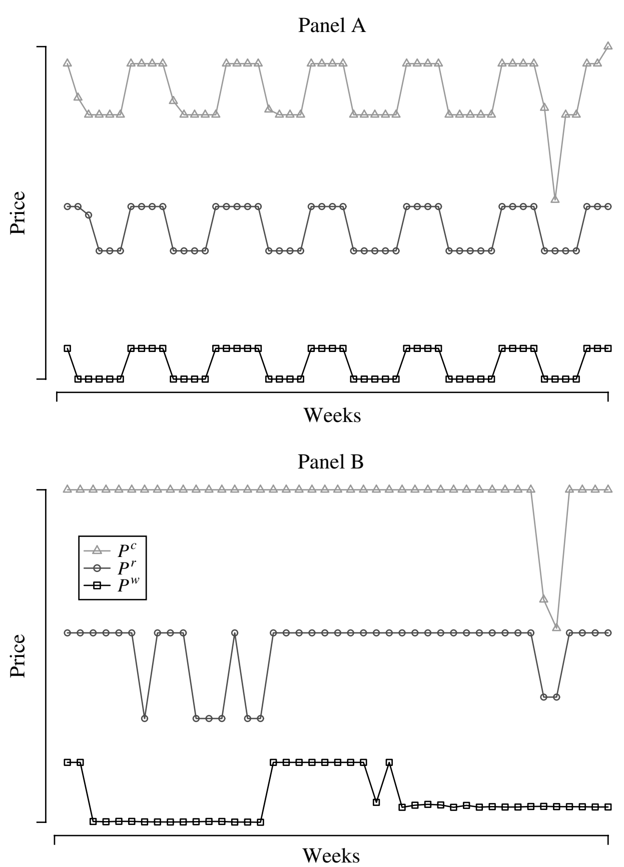


Table 2 **Measurement Details for Zs**

Variable	Measurement
Wholesaler cost of channel flows	
Service level	Percentage of shipments by a wholesaler of less than 5 units[w]
Distribution of sales	Percentage of outlets that cover 80% of wholesaler shipments[w]
Distance to retailer	Driving distance in miles from wholesaler to retailer[w]
Retailer cost of channel flows	
Bulk-breaking	Number of subpacks in the delivered package format[r]
Competition—wholesaler	
Wholesaler size	Average shipments per week in volume units (10,000)[w]
Multi-line wholesaler	Dummy variable (=1 for multi-line wholesaler)[w]
Competition—retailer	
Retailer size	Average category sales level in the store in volume units (1,000)
UPC share	Product share of category sales at the store
Price elasticity	Price elasticity of consumer demand for the product*
Demand clout	Aggregate cross-sales effect from product price change*
Competitive structure	Herfindahl index of competing outlets in zip-code area
Control variables	
Key consumer segment	Percentage of population in zip in heavy user demographic
Average age	Average age in zip
Median income	Median household income in zip
Package material	Dummy variable (=1 for material A)
Package size	Number of units in package
Trade deal frequency	Percentage of weeks the product is on deal (>10% below regular price)[w]
Trade deal depth	Average depth of deal (%) offered to the retailer[w]

[w] W-to-R model only.
[r] R-to-C model only.
*To account for parameter uncertainty pass-through and demand equations are estimated simultaneously. A detailed description of the demand system is provided in Appendix B.

A wholesaler serving a small number of large retailers may attain cost efficiencies. We compute the *distribution of sales* as the percentage of outlets covering 80% of sales, 21% on average in our data. A sensitivity analysis confirms that our results are robust to alternative cutoff points for both *service level* and *distribution of sales*. The distance from the wholesaler's warehouse to retail outlets is measured by *distance to the retailer*. The average wholesaler-to-retailer distance is 28.15 miles.

Table 3 Descriptive Statistics for *Z*s

Statistic	Mean	Standard deviation
Wholesaler cost of channel flows		
Service level	24%	7%
Distribution of sales	21%	3%
Distance to retailer	28.15	28.48
Retailer cost of channel flows		
Bulk-breaking	1.68	0.63
Competition—wholesaler		
Wholesaler size (10,000)	—	3.34
Multi-line wholesaler	—	
Competition—retailer		
Retailer size (1,000)	1.09	0.49
UPC share	0.59%	0.69%
Price elasticity	−3.14	1.43
Demand clout	−0.01	0.24
Competitive structure	0.12	0.09
Control variables		
Key consumer segment	34%	3%
Average age	35.84	4.27
Median income ($000)	45.73	15.75
Package material	56%	
Package size	—	5.66
Trade deal frequency	26%	24%
Trade deal depth	13%	7%

Note. The percentage of multi-line wholesalers and the average wholesaler size and package size are not reported for confidentiality reasons.

Bulk-breaking is a labor-intensive task that adds to retailer costs. Some units must be broken into smaller components by the retailer before being offered to the consumer. The variable *bulk-breaking* captures the number of items in a unit, 1.68 on average in our data.

4.1.2. Competition. Measures of channel power, retail concentration, and price sensitivity are used to capture the various dimensions of competition. Firm size is a commonly used indicator of channel power, which we measure using average weekly wholesaler (*wholesaler size*) and retailer (*retailer size*) sales volume. Large wholesalers and retailers generally have more channel power.

When designing the channel, manufacturers decide on the degree of exclusive dealing by wholesalers. For wholesalers representing competing brands, an agency problem may arise. Retailer brand switching induced by trade deal pass-through may cause cannibalization for nonexclusive wholesalers. Also, because revenue for exclusive wholesalers depends on a single manufacturer, we expect them to have less channel power and pass-through more. *Multi-line wholesaler* is a dummy variable that indicates whether a wholesaler works exclusively with one manufacturer.

UPC share is a product's average share of category sales at a retail outlet. Because the category consists of hundreds of items, the mean share is low at 0.59%. We measure *price elasticity* in a log-log regression model using weekly retail price and quantity sold (see Appendix B for specification details). The average price elasticity is −3.14 and shows significant variability across products, retailers, and states (standard deviation equal to 1.43). Moreover, we include a measure of *demand clout*, which we define as the ability to steal sales from competing products following a price change. Although manufacturers often benefit from promoting a product with high clout, retailers may not. Generally speaking, retailers benefit from deals that induce category expansion, i.e., high price elasticity and low demand clout. The average value of demand clout in our data is −0.01. Histograms of price elasticity and demand clout are shown in Figure 2.

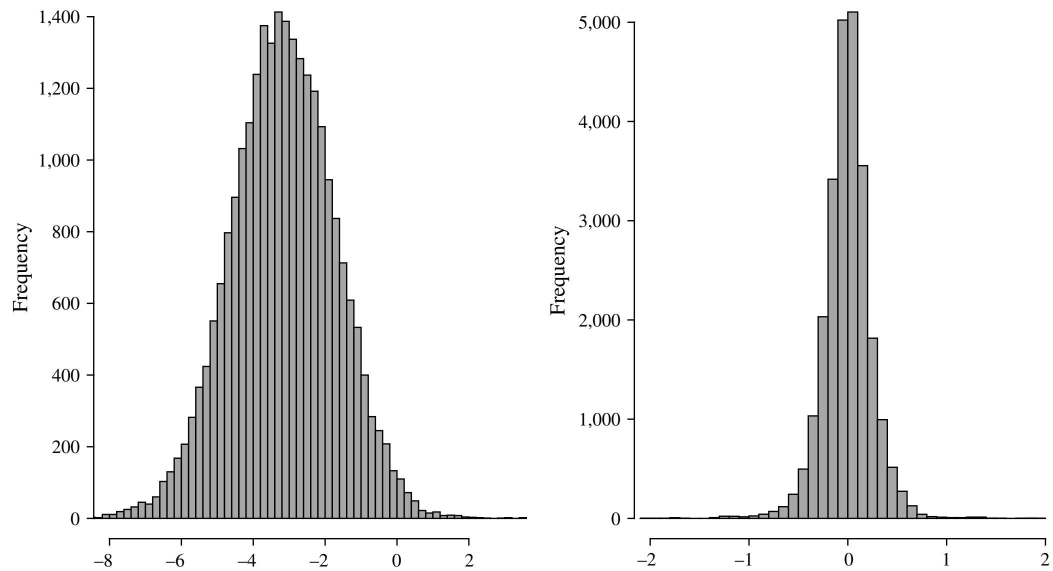
Finally, we use the Herfindahl index to capture *competitive structure* in a retail market (i.e., the sum of squared retail sales shares in a zip code area). We observe both consumer sales for a subset of retailers and shipment data to every outlet selling the products studied, allowing us to produce a complete picture of market competition. The average value of the Herfindahl index in our data is 0.12.

4.1.3. Control Variables. The demographic variables *average age* and *median income* are included as controls in our models. Across the retail areas in our study, the average age is 35.8 years and the average income is $45,730. The variable *key consumer segment* captures the proportion of heavy users of the products studied in a zip code. An analogy helps clarify the definition. Manufacturers of gaming systems, such as the Xbox, Wii, etc., might consider teen males as their primary target market. In our study an average of 34% of consumers in a zip code area is in the category's key consumer segment. Confidentiality restrictions prevent us from describing this group in more detail.

We also include two product characteristics in our models. *Package size* is the number of individual items in a product's consumer packaging, and *package material* is a dummy variable distinguishing the packaging material used (e.g., cardboard versus plastic).

Frequency and depth of trade promotions offered to retailers may impact pass-through estimates in the R-to-C model. To construct these variables we first define the regular wholesale price as the 95th percentile of P^r. Any wholesale price 10% below its regular value is defined as a promotion. *Trade deal frequency* is measured as the number of promotions divided by the number of observations in the time series. *Trade deal depth* is the average discount from the regular wholesale price during a promotion. On average, trade promotions occur in 26% of the weeks and reduce wholesale price by 13%.

Figure 2 **Histogram of Price Elasticity and Demand Clout**



(a) Price elasticity

(b) Demand clout

5. Results

We estimate the hierarchical model defined by Equations (4)–(8) and obtain the 23,147 pass-through elasticity estimates summarized in §5.1. We compare pass-through results using economic marginal cost (i.e., transaction cost) and accounting cost (i.e., average acquisition cost) in §5.2, and seek to explain the variation in pass-through across wholesalers, retailers, products, and geographies in §§5.3 and 5.4. Finally, we assess model fit and specification.

5.1. Pass-Through Estimates

We summarize our study's large number of parameter estimates in a series of histograms and Table 4. In Figure 3 we plot the histogram of the θ_{wrp} estimates for the W-to-R model. The intercept has a mean of 1.01 and a median of 0.94. In our log-log model the slope parameter can be interpreted as the W-to-R pass-through elasticity, which has a mean of 0.71 and a median of 0.75. The histogram shows a significant amount of variation in pass-through across wholesalers for different products and retailers.

Table 4 **Pass-Through Estimates**

	W to C			W to R			R to C		
Statistic	β	α	$\partial p/\partial c$	β	α	$\partial p/\partial c$	β	α	$\partial p/\partial c$
Mean	0.41	1.84	0.73	0.71	1.01	1.06	0.59	1.23	0.69
10th percentile	0.09	1.03	0.16	0.34	0.29	0.53	0.21	0.20	0.25
25th percentile	0.22	1.47	0.39	0.54	0.59	0.86	0.38	0.67	0.45
Median	0.39	1.89	0.69	0.75	0.94	1.13	0.58	1.25	0.67
75th percentile	0.58	2.26	1.02	0.91	1.39	1.34	0.80	1.80	0.92
90th percentile	0.78	2.55	1.36	1.02	1.83	1.46	0.98	2.22	1.14
No. of observations	23,147			23,147			23,147		

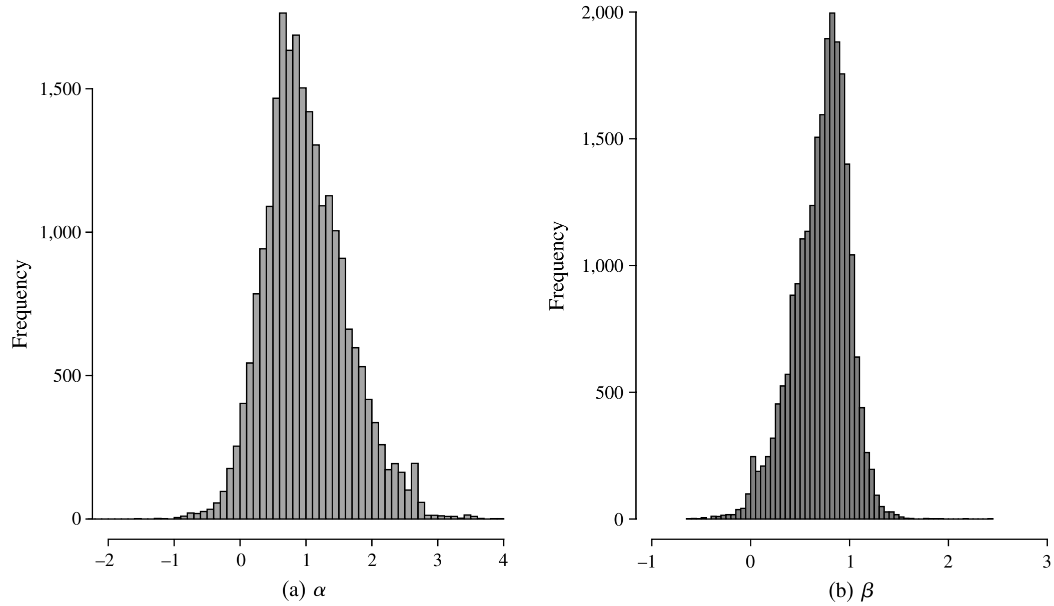
In Figure 4 we plot the histogram of the parameter estimates for the R-to-C model. The intercept has a mean of 1.23 and a median of 1.25. Again, the main variable of interest is the slope parameter, which has a mean of 0.59 and a median of 0.58. Similar to the W-to-R model we find considerable variation in retail pass-through, which we explore in §5.4.

To compute the overall pass-through elasticity for the channel (W to C), we multiply the W-to-R and R-to-C pass-through estimates for each product. The mean W-to-C pass-through elasticity is 0.41 (median 0.39). Thus, a 10% reduction in manufacturer price results in an average reduction in consumer price of 4.1%, clearly demonstrating that a substantial percentage of trade deals offered by the manufacturer never reaches the consumer. Figure 5 shows a histogram of the W-to-R estimates.

To compare our results with previously published research, we convert pass-through elasticities to pass-through rates, i.e., $\partial p/\partial c$. A histogram is provided in Figure 6. At the W-to-R level the mean and median pass-through rates are 1.06 and 1.13, respectively. Pass-through rates greater than 1 imply that wholesalers earn lower margins in promotion periods. A \$1 manufacturer price decrease results in a \$1.06 decrease in the wholesale price paid by retailers. Therefore, a wholesaler with margin m has margin $m - 0.06$ in promotional periods, requiring a demand increase of $0.06/(m - 0.06)$ to break even.

Pass-through rates at the R-to-C level are substantially lower: the mean is 0.69 and the median is 0.67. When wholesalers offer a \$1 discount, retailers reduce the consumer price by \$0.69 on average, pocketing 31% of trade deal dollars. Our estimates

Figure 3 Histogram of α and β W to R



of pass-through rates are close to retailers' self-reported 67% and much higher than manufacturers' 45% (Cannondale 1998). Mean channel pass-through rates (W to C) equal 0.73 (median 0.69); when the manufacturer offers a $1 discount to the wholesaler, price to consumer decreases by $0.73.

Overall, when compared to retailers, wholesalers' pass-through rates and elasticities are significantly higher, suggesting manufacturers have more channel power over the latter than the former. At each channel level we find large variances in pass-through, clearly indicating that aggregate estimates of pass-through are of limited tactical value to manufacturers. For example, a retail chain's pass-through elasticity might equal 98% in California but 42% in Nevada. The average across these values has little meaning for a manufacturer evaluating promotional programs for the channel.

Finally, we investigate the link between retailer feature and display support, retailer pricing, and trade deal pass-through. Although we find that featured and/or displayed goods have a lower consumer price ($\lambda < 0$), they tend to receive less pass-through ($\gamma < 0$). By pocketing a larger percentage of a trade

Figure 4 Histogram of α and β R to C

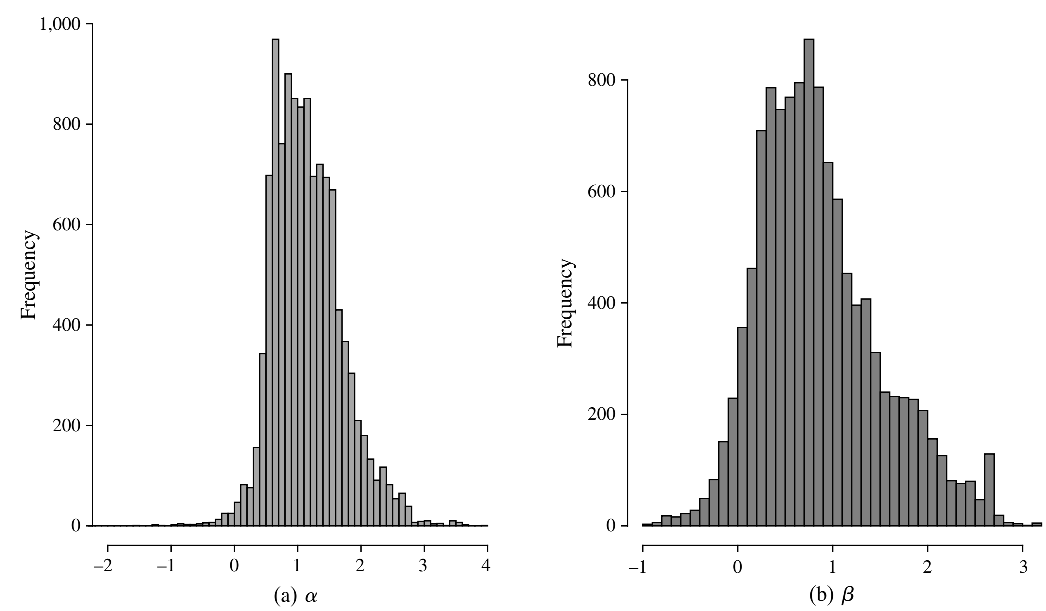
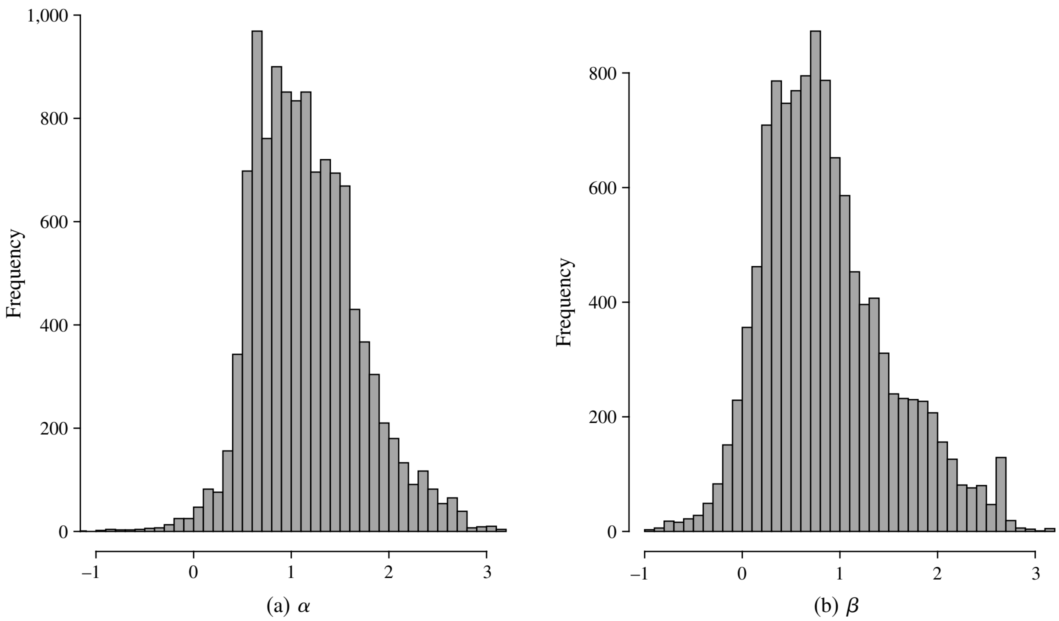


Figure 5 Histogram of α and β W to C



deal, retailers may force wholesalers to compensate for additional promotional costs incurred (Kim and Staelin 1999).

5.2. Cost Measures

Pass-through is measured by relating changes in the economic variable cost of a good to price changes at a lower level in the distribution channel. In our study the transaction cost is the economic variable cost. However, as mentioned above, four recent studies of pass-through (BDG, Meza and Sudhir 2006, Pauwels 2007, Dubé and Gupta 2008) have used an accounting metric, average acquisition cost (AAC), instead. Below we investigate how pass-through elasticity estimates are affected by the use of different cost metrics.

Before comparing estimates we first define AAC. Consider a series of discrete time periods t; t^0 denotes the start of period t, and t^- (t^+) represents the time just before (after) t^0. Next, consider a retailer setting prices in period t. We assume she measures inventory at time t^- and knows the price charged by the wholesaler, $P^r(t^-)$. She then sets consumer price $P^c(t)$ and determines the shipments required to cover demand. Shipments arrive at t^+ and the retailer observes consumer demand for period t. The inventory level at time $t^- + 1$ is calculated as shipments plus previous inventory minus sales. AAC is defined as

$$\begin{aligned}
&\mathrm{AAC}(t^- + 1)\\
&\quad = \big[\mathrm{Sales}(t) \text{ from Shipments}(t^+) \times P^r(t^-)\\
&\qquad + \mathrm{Sales}(t) \text{ from Inventory}(t^-) \times \mathrm{AAC}(t^-)\big]\\
&\qquad \times \mathrm{Inventory}(t^- + 1)^{-1}. \qquad (9)
\end{aligned}$$

Figure 6 Histogram of $\partial p/\partial c$

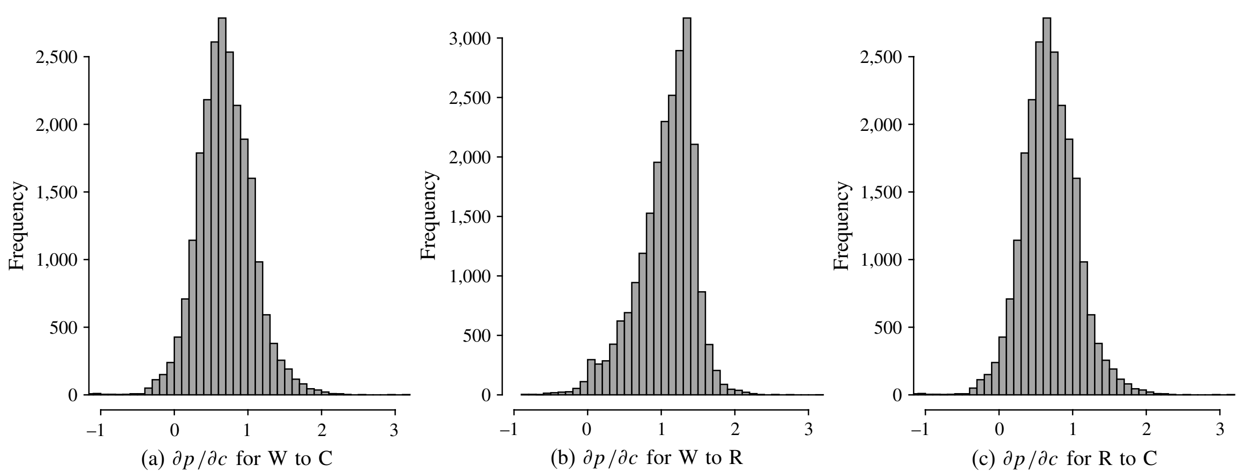


Table 5 **Pass-Through Estimates Using AAC and Transaction Cost for Periods in Which Both Are Known**

Pass-through	Mean	Median
Transaction cost	0.59	0.58
AAC	0.77	0.79

This definition highlights two major problems for estimating pass-through. First, because AAC captures the average value of products in inventory at the *end* of a period ($t^- + 1$) it cannot drive the consumer price set by the retailer at the *beginning* of the period (t^0). Moreover, the AAC value in a given week is a function of that period's consumer price $P^c(t)$, creating a clear endogeneity problem first recognized by Peltzman (2000).[6] Because lagged AAC does not incorporate the wholesale price offered to the retailer at t^- it is not an appropriate solution.

The problems mentioned above highlight important differences between accounting and economic cost metrics. Although AAC is an appropriate measure of inventory value at the end of a period, economic measures of cost (i.e., transaction cost) are needed to evaluate how cost changes affect price changes McAlister (2007). We define transaction cost as the price per volume unit paid by the retailer (wholesaler), which is equivalent to the spot price in a given week. Table 5 and Figure 7 show the pass-through estimates based on transaction cost and AAC in periods where both are known. The estimates are strikingly different: AAC induces a 31% upward bias in the mean and a 36% upward bias in the median pass-through elasticity.

Although AAC may be an important accounting measure for retailers, our empirical findings confirm the metric is ill suited for estimating pass-through. Our analyses suggest extant studies of pass-through should be interpreted with caution as they overstate the effectiveness of trade promotions.

5.3. Variation in Pass-Through from Wholesaler to Retailer (W to R)

In §5.1 we demonstrated considerable variation in pass-through, which we seek to explain below using measures of cost and competition. Table 6 contains the Δ estimates for the W-to-R model (see Equation (6)). Given the large number of observations it is not surprising that many variables are significant in explaining pass-through variation. To distinguish between "statistical significance" and "managerial importance," we calculate the scaled marginal impact of each variable, i.e., the effect of a one-standard-deviation increase in a Z variable on the pass-through elasticity.

[6] The definition of AAC shows that the inventory level and value at the end of a period ($t^- + 1$) are determined by the consumer price set at t^0. All else equal, inventory levels at $t^- + 1$ will be lower (higher) if the price to the consumer at t^0 is lower (higher). Keeping shipment size constant, the price to the consumer at t^0 will also influence the average value of goods in inventory at $t^- + 1$ if we assume the retailer uses a first-in-first-out (FIFO) warehouse policy. If $P^r(t^-) > \text{AAC}(t^-)$, the lower (higher) the consumer price set at t^0, the fewer (more) goods from inventory at t^- will be left over at $t^- + 1$, resulting in a higher (lower) $\text{AAC}(t^- + 1)$ value. Similarly, if $P^r(t^-) < \text{AAC}(t^-)$, the lower (higher) the consumer price set at t^0, the fewer (more) goods from inventory at t^- will be left over at $t^- + 1$, leading to a lower (higher) $\text{AAC}(t^- + 1)$ value.

Figure 7 **Pass-Through Estimates Using AAC and Transaction Cost for Periods in Which Both Are Known**

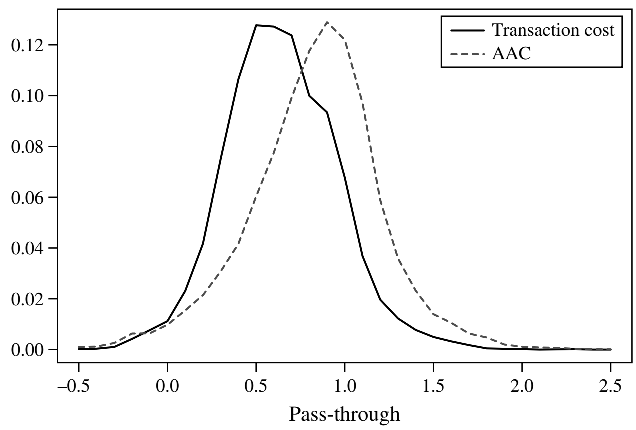


Table 6 **Estimates of Δ, W to R**

Variable	Std. par.	Mean	Hypothesis
Wholesaler cost of channel flows			
Service level	−0.092	−1.303**	−
Distribution of sales	−0.014	−0.453**	−
Distance to retailer	−0.004	−0.0001*	−
Competition—wholesaler			
Wholesaler size (10,000)	−0.090	−0.027**	−
Multi-line wholesaler		0.075**	−
Competition—retailer			
Retailer size (1,000)	0.005	0.010*	+
UPC share	0.019	2.764**	−
Price elasticity	−0.001	−0.001	−
Demand clout	0.001	0.005	+
Competitive structure	0.005	0.054**	+
Control variables			
Key consumer segment	−0.002	−0.046	
Average age	0.006	0.001**	
Median income ($000)	0.002	0.000	
Package material		0.048**	
Package size	−0.040	−0.007**	
R^2	0.30		

Notes. The table shows the posterior mean of each parameter. The column labeled "Std. par." shows the effect of a one-standard-deviation increase in the corresponding Z variable on pass-through. Z includes fixed effects for brand, retail chain, and state.

*Zero is contained in the 99% but not in the 95% credibility region.

**Zero is not contained in the 99% credibility region.

5.3.1. Wholesaler Cost of Channel Flows. We explore the link between several measures of wholesaler cost and pass-through. Because the average pass-through rate is 1.06, wholesalers require a demand increase to break even on a trade deal (see §5.1). Costs of channel flows diminish margins and further necessitate such demand increases, likely lowering the pass-through of trade deals. Although each effect is statistically significant, the marginal effects reveal considerable variation in managerial importance.

We find that a one-standard-deviation increase in wholesaler *service level* lowers pass-through by more than 9.2%. Wholesalers delivering many small orders incur higher costs than those who deliver fewer but larger quantities. Because the former have lower margins and require a greater demand increase to break even on an accepted trade deal, they pass through less.

A one-standard-deviation increase in the *distribution of sales* yields a 1.4% decrease in pass-through. Concentrated markets may create logistical efficiencies and lower operational costs for the wholesaler, enhancing the likelihood of trade deal pass-through.

Wholesalers pass through less to retailers located further away. A one-standard-deviation increase in *distance to the retailer* decreases pass-through by 0.4%, which suggests that wholesalers seek to recover high delivery costs. However, of the cost metrics considered, distance has the smallest impact.

5.3.2. Competition—Wholesaler. *Wholesaler size* has a significant negative impact on the extent of pass-through. A one-standard-deviation increase in wholesaler size decreases pass-through by 9.0%. Because firm size and channel power are correlated, manufacturers tend to have more influence over small wholesalers leading to higher trade deal pass-through. Because larger wholesalers may be more sophisticated and better able to assess the benefits and costs of accepting a trade deal, they are less likely to fully participate when manufacturers offer unattractive deals.

In the category studied, some wholesalers partner exclusively with one manufacturer while others do not. Contrary to theories predicting that nonexclusive agreements between manufacturer and wholesaler can lead to incentive conflicts (Bernheim and Whinston 1998), our results show that *multi-line wholesalers* pass through 7.5% more to the retailer.

5.3.3. Competition—Retailer. Consistent with our result on channel power and firm size, we find that wholesalers pass through more to larger retailers. However, the effect is small: a one-standard-deviation increase in retailer size increases wholesaler pass-through by 0.5%.

We find that *UPC share* enhances wholesaler pass-through. A one-standard-deviation increase in share boosts pass-through by 1.9%. Because wholesalers require a demand increase to break even on a trade deal (see §5.1), an increase would be expected if retailers pass through more for leading brands. Alternatively, one could argue that share should decrease pass-through if the popularity of a product in the retailer's assortment offers more channel power to the wholesaler.

From economic theory we would expect the impact of *price elasticity* to be negative and of *demand clout* to be positive. However, we find that neither have a significant effect on wholesaler pass-through.

A one-standard-deviation increase in *competitive structure* (i.e., a decline in competition) increases the level of wholesaler pass-through by 0.5%, consistent with the effect of *distribution of sales* reported above. Because retailers have less power relative to the wholesaler in competitive markets, the latter has less incentive to pass through trade deals. The opposite holds in less competitive markets with fewer and larger retailers, in line with results on wholesaler and retailer size.

Most surprising about our results are the small marginal effects of *price elasticity*, *demand clout*, and *competitive structure* (0.1%, 0.1%, and 0.5%, respectively). Although our model supports some long-standing predictions from economic theory, the "action" is elsewhere.

5.3.4. Control Variables. *Average age* is the only demographic variable that significantly influences wholesaler pass-through. A one-standard-deviation increase in the average age in a zip code area increases pass-through by 0.6%. Whereas *package size* has a negative effect on pass-through, *package material* has a positive impact.

To summarize, the most important components driving variation in pass-through in the W-to-R model are (1) wholesaler cost and (2) wholesaler characteristics linked to channel power and competition. These findings illustrate the importance of understanding the wholesaler's role in channel pass-through, a key contribution of our paper. Interestingly, measures of competition at the retail level have limited impact.

5.4. Variation in Pass-Through from Retailer to Consumer (R to C)

Table 7 contains estimates of the Δ coefficients for the R to C model. Again, we emphasize both the statistical and economic significance of all variables.

5.4.1. Retailer Cost of Channel Flows. Retailers pass through less on products that require *bulk-breaking* to cover additional costs. A one-standard-deviation increase in the number of items in the

Table 7 **Estimates of Δ, R to C**

Variable	Std. par.	Mean	Hypothesis
Retailer cost of channel flows			
Bulk-breaking	−0.019	−0.030**	−
Competition—retailer			
Retailer size (1,000)	0.012	0.024**	−
UPC share	0.010	1.507**	+
Price elasticity	−0.009	−0.006**	−
Demand clout	−0.009	−0.037**	−
Competitive structure	0.000	0.004	−
Control variables			
Key consumer segment	−0.004	−0.124	
Average age	0.001	0.000	
Median income	0.001	0.000	
Package material		−0.091**	
Package size	0.020	0.003**	
Trade deal frequency	−0.056	−0.229**	
Trade deal depth	0.002	0.034	
R^2	0.37		

Notes. The table shows the posterior mean of each parameter. The column labeled "Std. par." shows the effect of a one-standard-deviation increase in the corresponding Z variable on pass-through. Z includes fixed effects for brand, retail chain, and state.

*Zero is contained in the 99% but not in the 95% credibility region.

**Zero is not contained in the 99% credibility region.

original unit leads to a 1.9% decline in pass-through. Consistent with the results at the W-to-R level, higher costs are associated with lower pass-through.

5.4.2. Competition—Retailer. Surprisingly, a one-standard-deviation increase in *retailer size* leads to a 1.2% increase in retailer pass-through even though large, powerful retailers might be expected to pass through less. On the other hand, large retailers benefit from passing through deals when the corresponding consumer demand increase is large in absolute terms. Furthermore, because retailers with higher category sales may be more efficient and able to spread overhead across many products, they may not need to pocket trade dollars to cover costs.

Even though empirical studies on pass-through are rare, *UPC share* has received some attention in the literature. Consistent with previous studies we find *UPC share* has a positive and statistically significant impact on pass-through, but the marginal effect is small (i.e., 1% for a one-standard-deviation increase in share).[7]

A one-standard-deviation decrease in *price elasticity* (i.e., more negative) leads to a 0.9% increase in retailer pass-through. This result supports established economic theory that more competitive markets have higher levels of retailer pass-through. Interestingly, retailers pass through less on products with higher *demand clout*. Generally speaking, retailers stand to gain from category expansion, not brand switching. Consistent with the results for the W-to-R model, the marginal effects of price elasticity and clout for the R-to-C model are small; the action is elsewhere. Finally, even though *competitive structure* is expected to influence pass-through, we did not find any support for this prediction.

5.4.3. Control Variables. None of the demographic control variables has a significant effect on retailer pass-through to the consumer. We investigate the role of two product characteristics in retailer pass-through: *package size* and *package material*. Both are statistically significant but differ in managerial relevance. A one-standard-deviation increase in *package size* leads to a 2.0% increase in pass-through. The variable with the most significant impact on retail pass-through is *package material*. Products in package material A, receive 10% less pass-through.[8] It is interesting to note, however, that for products in package material A, the retailer passes through less while the wholesaler passes through more, which enhances the retailer's bottom line.

We find that *trade deal frequency* has a significant negative impact on pass-through. A one-standard-deviation increase in trade deal frequency leads to a 5.6% decrease in pass-through. Finally, *trade deal depth* has an insignificant effect on pass-through.

To summarize, the most important factors determining retailer pass-through are (1) package material, (2) bulk-breaking, and (3) trade deal frequency. Somewhat surprisingly, competition has limited impact on pass-through; the effects were either statistically insignificant or managerially irrelevant.

5.5. Model Fit and Specification

To assess model fit we computed both within and out-of-sample statistics. The median R^2 for the W-to-R model is 70% (25th percentile—44%, 75th percentile—87%) and the median R^2 for the R-to-C model is 48% (25th percentile—32%, 75th percentile—65%). The covariates described in §4.1 explain 30% of the variability in pass-through for the W-to-R model and 37% for the R-to-C model.

Out-of-sample tests were conducted by re-estimating our models on 75% of the data and comparing predictions to pass-through estimates obtained using the full data. The correlation between estimated and predicted pass-through is 0.55 for the W-to-R model and 0.59 for the R-to-C model. The median difference in estimated and predicted pass-through for the W-to-R model is 0.032 and 0.003 for the R-to-C model.

[7] This result does not support the assumption of an inverse relationship between pass-through and product share made in some structural models (e.g., Sudhir 2001).

[8] Because of confidentiality restrictions, we cannot reveal the packaging materials.

We performed three model specification checks. First, we assessed if our results are affected by omitting cross-brand pass-through. Because these effects cannot be estimated for hundreds of UPCs, we were unable to include them in our models. BDG restricted their analysis to the categories' top-selling UPCs; we followed a similar approach and limited our analysis to the best-selling package size for the top three brands in our data. We found both positive and negative cross-brand pass-through effects. More importantly, own-brand pass-through estimates derived from a model with and without cross-brand effects were statistically indistinguishable.[9]

Because our model covers multiple geographic regions, we also checked for spatial correlation by evaluating if the absolute difference between stores in the size of the errors from the second stage of our hierarchical model is related to the distance between them. In our application no significant spatial correlation was found. The overall correlation was equal to 0.0007 ($p = 0.48$), whereas the correlations for the individual stores ranged from −0.040 to 0.048 (none was significant). The application of Kriging methods further confirmed that spatial correlation in the second-stage errors is negligible (Bronnenberg 2005).

Finally, we investigated if missing observations affect our pass-through estimates. Whereas fast-moving consumer goods typically ship every week, less frequently purchased items may not. Transaction costs are only observed when transactions occur. Studies using store-level scanner data face a similar problem as prices are not observed in weeks without consumer sales. We compared the pass-through estimates reported in Table 4 with those obtained when missing transaction cost values were replaced by the last observed transaction cost.[10] Our earlier estimates of the mean and median R-to-C pass-through are 0.59 and 0.58, respectively, whereas the mean and median estimates using the imputed data series are 0.58 and 0.59, respectively. In a further validation exercise, we used Bayesian model-based imputation and found very similar results; mean and median pass-through of 0.56 and 0.56, respectively. Both robustness checks demonstrated that unobserved cost values do not influence our pass-through estimates.

6. Managerial Implications

In this paper we measured pass-through and explained its variation across a large number of products and markets. We now ask how insight into pass-through levels can enhance the efficient use of promotion budgets. To answer this question we consider two scenarios. In the first, we assume the manufacturer offers all retailers the same trade deal on all products, which we refer to as an *inclusive* promotion strategy. In the second scenario the manufacturer only offers trade promotions that result in increased manufacturer profits, which we label a *selective* promotion strategy. We compute expected profits for both scenarios using information on margins and the estimates of pass-through and price elasticity discussed above. A comparison of costs and profits between the two promotion strategies allows us to establish an upper bound on the value of pass-through measurement.

Figure 8 below depicts outcomes for a 10% off invoice retailer deal in the first scenario.[11, 12] The contrast between manufacturer and retailer profits is striking. Although an inclusive trade deal strategy decreases manufacturer profits in the majority of cases (56%), it increases retailer profits in 96% of cases. The relationship between deal profitability, pass-through, and price elasticity is unmistakable. All else equal, higher levels of retailer pass-through and demand response are attractive for the manufacturer. A somewhat different pattern is observed for retailers: the profit increase is largest when demand is highly elastic and pass-through is less than 100%.

In the second scenario the manufacturer only provides trade deals that are expected to increase her profits (see Figure 9), which results in a 56% reduction in the number of retailers and products receiving deals. Interestingly, 95% of retailers that do receive a trade deal in the selective promotion scenario still experience a profit boost.

Manufacturer profitability could improve 80% on a 10% deal by switching to a selective from an inclusive promotion strategy. However, because fewer retailers and products qualify, retailers as a group would lose 50% of profits from manufacturer trade dollars. Nevertheless, as stated above, those that would still receive deals achieve a performance boost in the vast majority of cases.

In addition to profit increases, the selective trade deal strategy would also result in cost savings. When total promotional cost is calculated as deal size times demand under deal conditions, manufacturers could achieve 40% cost savings on 10% off invoice trade deals. As U.S. trade deal spending exceeds $75 billion annually, savings generated by trade deal effectiveness estimation could be substantial.

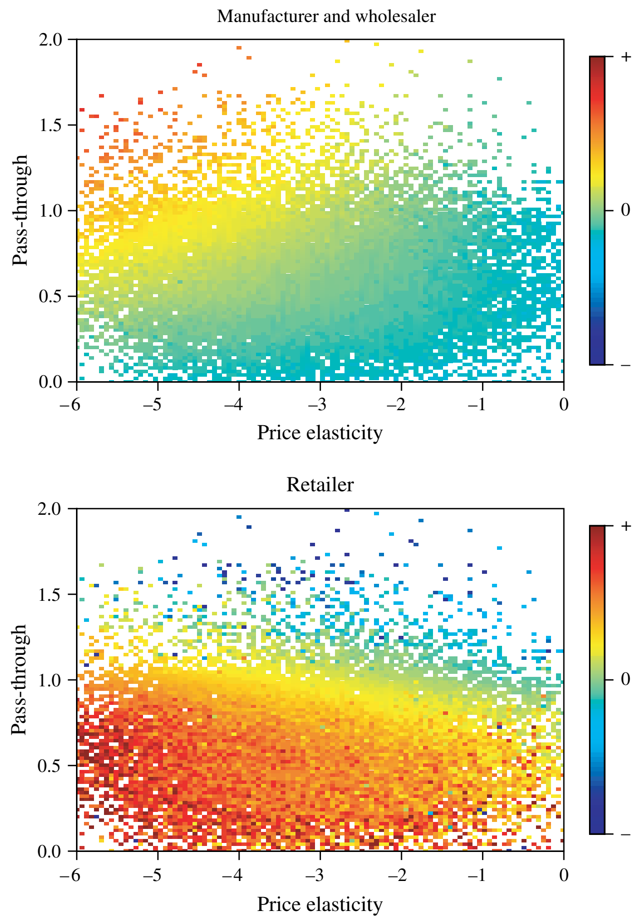
[9] Augmenting models of pass-through with cross-brand effects may be of greater importance in other empirical settings.

[10] The latter may not reflect true replacement cost in periods without wholesaler shipments.

[11] We use identical scales for all figures in this section.

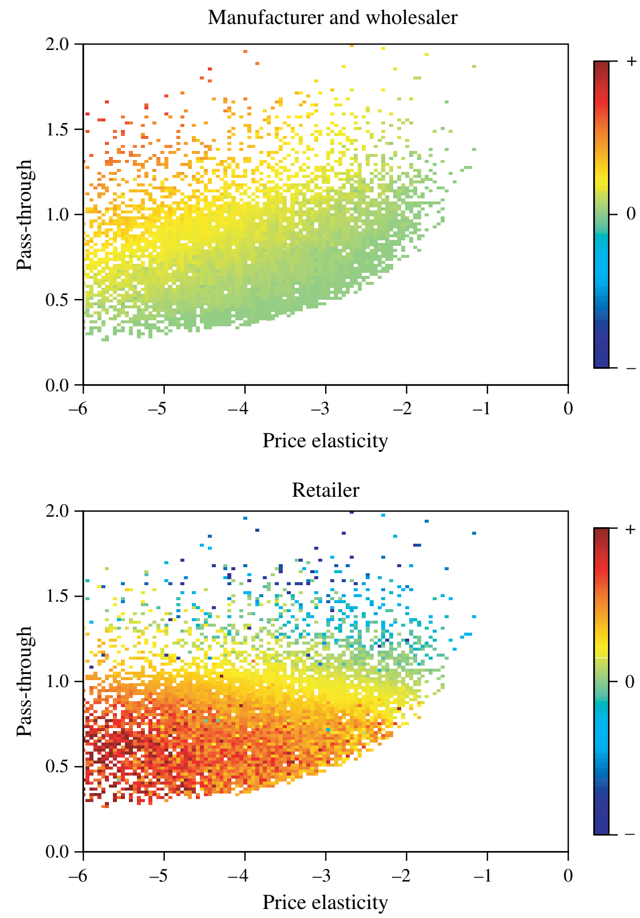
[12] For reasons of confidentiality we neither separate manufacturer and wholesaler results, nor disclose the actual percentage of profitable deals offered. Reporting the effects for manufacturer and wholesaler jointly facilitates comparison with direct-to-store-delivery markets.

Figure 8 Profitability Change Under an Inclusive Trade Deal Strategy for a 10% Deal



Notes. For each product/store combination, profits under deal and no-deal conditions are calculated using margins and price and pass-through elasticities. The graphs show the percent change in profits under deal versus nondeal conditions for an inclusive trade deal strategy. Legend values have been removed for reasons of confidentiality.

Figure 9 Profitability Change Under a Selective Trade Deal Strategy for a 10% Deal



Notes. The graphs show the percent change in profits under deal versus nondeal conditions using a selective trade deal strategy. Legend values have been removed for reasons of confidentiality.

Based on personal conversations with managers and the dispute between retailers and manufacturers on the actual level of pass-through, we infer that few manufacturers currently achieve efficiencies at the level of the selective trade-spending strategy. Similarly, few would manage their spending as inefficiently as the inclusive trade deal strategy implies. Our results should therefore be taken as an upper bound on profitability improvements and cost reductions channel members could achieve by using trade deals more selectively.

The question remains why trade deals in the inclusive scenario fail to enhance profits for the manufacturer in the majority of cases (cases included in Figure 8 but excluded from Figure 9). Previous research suggests demand conditions (i.e., inelastic consumer demand) and strategic retail behavior (i.e., limited pass-through) are likely causes, but their relative influence on trade deal effectiveness has not yet been quantified. We calculate the mean price and pass-through elasticities for product/store combinations when trade deals used as part of an inclusive strategy would or would not enhance manufacturer profits. We find that demand is significantly more elastic for profitable (−4.01) than nonprofitable cases (−2.45) and pass-through elasticities are much higher for the former than the latter (0.78 versus 0.44), suggesting both forces play an important role.

To establish the relative influence of demand conditions and strategic retailer behavior, we calculate the percentage of previously unprofitable cases that could turn profitable if retailers passed through 100%. Our results show that 37% of unprofitable manufacturer and wholesaler deals are the result of insufficient pass-through on the part of the retailer. The majority (63%) can, however, be attributed to inelastic demand and cost conditions. By identifying why a trade deal is unprofitable, a manufacturer may be able to take corrective action.

It is important to note that a purely selective trade deal strategy may not be feasible in practice because of restrictions imposed by the Robinson-Patman Act. However, even when wholesalers are restricted to offering the same deal for a specific UPC to all retailers within their trading area, profits improve by 59% on a 10% deal compared to an inclusive trade deal strategy. Also, seemingly unprofitable deals may provide other benefits to manufacturers such as distribution and shelf space.

In sum, we establish an upper bound on the value of pass-through measurement. We show that, relative to an inclusive strategy, selective use of deals can increase profits and significantly reduce costs for manufacturers and wholesalers while still providing monetary benefits to the vast majority of retailers. However, the extent to which manufacturers and wholesalers measure pass-through remains to be seen.

7. Conclusions

Manufacturers and retailers take radically different views on the level of trade deal pass-through in practice. Manufacturers believe there is very little pass-through while retailers argue they receive insufficient trade dollars. In this paper we studied the effectiveness of trade promotions by quantifying pass-through at multiple levels of the distribution channel. Given the managerial importance of trade deals, the scarcity of empirical research in this area is surprising. Although estimated pass-through elasticities for the three-tier channel are 41%, pass-through rates from retailer to consumer are close to retailers' self-reported 67% and much higher than manufacturers believe. We find that the mean pass-through elasticities are 0.71, 0.59, and 0.41, for the wholesaler, retailer, and total channel, respectively. Because large variances in the estimates of pass-through elasticities are observed at all channel levels, we argue that average values are of limited tactical value to manufacturers.

We critique the use of accounting metrics in previous studies (BDG, Meza and Sudhir 2006, Pauwels 2007, Dubé and Gupta 2008) and show that AAC induces a strong upward bias in pass-through estimates (31%). Our finding suggests that the effectiveness of trade promotions has most likely been overstated in previous studies. However, given the high correlation between AAC and transaction costs, it can serve as a proxy in many other research settings.

Our research helps manufacturers understand the sources of variation in pass-through and improve trade deal effectiveness, which is an important contribution because previous studies (e.g., BDG, Meza and Sudhir 2006) did not address wholesaler and retailer pass-through under varied market conditions. Competitive position and costs of channel flows are the most important components driving variation in pass-through by wholesalers. Because larger wholesalers pass through less, manufacturers could benefit from assigning smaller territories.

Delivery service level is the biggest effect on the cost side. Wholesalers providing more service (i.e., smaller shipments more frequently) pass through less. Although fill-in deliveries reduce the likelihood of stock-outs, they also limit manufacturer control over wholesale prices. We offer manufacturers a useful metric to evaluate the trade-off between product availability and pricing control.

The most compelling theory used to predict pass-through variation suggests a positive association between levels of retail competition and pass-through (Heflebower 1957). Although our analysis supports several hypothesized effects of competition, their managerial relevance is limited with standardized marginal effects below 1%; the action is elsewhere. The influence of wholesalers on pass-through has important implications for channel design and trade promotion strategies, one of our paper's key contributions for researchers and managers alike.

Furthermore, channel flow costs are an important determinant of pass-through by the retailer. Because bulk-breaking reduces retailer pass-through, manufacturers and wholesalers face a trade-off. Although delivering in bulk reduces costs, our results show it limits pricing control and consumer benefits of trade deals. Manufacturers should augment our findings with internal cost data to determine where this trade-off levels out. Again, our results confirm established theories that link competition and pass-through. Products with the strongest market position (*UPC share*) receive most pass-through. Whereas pass-through is higher when demand is more elastic and lower when the product on deal cannibalizes sales of others, effect size is limited.

Although our study does not claim to settle the larger debate between manufacturers and retailers about the level of trade deal pass-through, we are able to quantify the benefits of retailer pass-through measurement for manufacturers and wholesalers. We show that selective trade promotion spending based on accurate pass-through estimates can significantly improve trade deal profitability and reduce promotional costs. We also demonstrate that unprofitable manufacturer and wholesaler trade deals are more likely caused by demand conditions than strategic retail behavior.[13] These insights will benefit manufacturers and wholesalers in trade deal and pass-through

[13] The clear influence of the price elasticity of demand on manufacturer and wholesaler profitability of trade-deals seems inconsistent with the finding reported in §5.3 that the level of wholesaler pass-through is not linked to price elasticity at the retail level. Future research should seek to explain this intriguing result.

negotiations with retailers. Although manufacturers and wholesalers have limited influence on price elasticities, they can use a variety of deal contracts, such as scan-backs (Drèze and Bell 2003), to enhance channel coordination and influence retailer pass-through.

Our findings complement extant research on pass-through and suggest additional areas for future research. The minimal influence of competitive structure on retailer pass-through is intriguing and merits further investigation. Whereas our study focuses on trade deals, pass-through of regular cost changes should also be addressed in future research. McAlister (2007) claims the extent of cross-brand pass-through documented in BDG may be biased by the use of AAC as a cost metric. A thorough exploration of cross-brand pass-through using transaction cost data rather than accounting metrics should be conducted. Dubé and Gupta (2008, p. 332) state that "Ultimately, the scientific approach to resolving the debate over cross-brand pass-through would be to encourage the collection of better measures of wholesale prices . . . ."

The scope of any study's results is limited by the breadth of available information. We hope our findings help manufacturers recognize the value of research on pass-through and encourage them to share data with academics who may extend our insights to additional markets and channel structures.

Appendix A. Specification of Priors

Each wholesaler-retailer-product combination is a linear regression model with common variance. The prior distribution for the hyper-prior parameters is as follows: $\Omega \sim IW(v, V)$ and $\Delta \mid \Omega \sim N(\bar{\Delta}, \Omega \otimes A^{-1})$. We set $v = \#\text{covariates} + 2$, $V = vI$, $\bar{\Delta} = 0$, and $A = 0.001I$. The hyper-priors for the variance are as follows: $\sigma_\sigma^2 \sim IW(3, 5)$ and $\sigma_\mu \mid \sigma_\sigma^2 \sim N(0, \sigma_\sigma^2 * 0.001)$. Note that a one dimensional inverse Wishart distribution is an inverse chi-squared distribution. The results are insensitive to the prior parameter values because of the large number of data points. We use a Markov chain Monte Carlo (MCMC) algorithm of the Gibbs sampler form to simulate posterior distributions of the parameters of interest. We run the MCMC algorithm for a total of 10,000 iterations, using the last 5,000 for inference. Because we use a standard linear hierarchical Bayesian model, we refer to Rossi et al. (2005) for further details on the estimation algorithm.

Appendix B. Demand System

We specify two store-level consumer demand systems: one to estimate price elasticity, the other to quantify demand clout. The first is given by

$$\log(Q_{rpt}) = \beta_{rp}\log(P_{rpt}) + \gamma_{rp}\log(P_{r-pt}) + \lambda_{rp}FD_{rpt} + \epsilon_{rpt}, \quad \text{(B1)}$$

where Q_{rpt} is retail demand for product p in store r at time t, P_{rpt} is consumer price, β_{rp} is the price elasticity of demand, FD_{rpt} is the level of feature and display activity, and P_{r-pt} is a weighted average price for every other product sold in store r at time t. Seasonal variation as well as store and product-specific fixed effects are also accounted for. The second demand system is given by

$$\log(Q_{r-pt}) = \beta_{rp}\log(P_{rpt}) + \gamma_{rp}\log(P_{r-pt}) + \lambda_{rp}FD_{rpt} + \epsilon_{rpt}, \quad \text{(B2)}$$

where Q_{r-pt} is retail demand for every product other than p in store r at time t, and the other variables are as before. The parameter of interest is β_{rp}, which captures demand clout. Similar to the pass-though models discussed in §3, we model the demand system parameters as

$$\theta_{rp} \mid \theta_r, \theta_p, \Omega \sim \mathrm{N}(\theta_r + \theta_p, \Omega), \quad \text{(B3)}$$

where θ_{rp} is the 3-tuple $(\beta_{rp}, \gamma_{rp}, \lambda_{rp})$, and θ_r and θ_p capture store- and product-specific mean effects. For identification we set these equal to zero for one retailer. The error structure is the same as for the pass-through models.

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