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Pass-through timing*

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Abstract Trade promotions are the most important promotional tool available to a manufacturer. However trade promotions can achieve their objective of increasing short-term sales only if the retailer passes through these promotions. Empirical research has documented that there is a wide variation in retail pass-through across products. However little is known about *the variations in pass-through over time.* This is particularly important for products with distinct seasonal patterns. We argue that extant methods of measuring pass-through are inadequate for seasonal products. We therefore introduce a measurement approach and illustrate it using two product categories. We find interesting differences in pass-through for loss-leader products versus regular products during high demand and regular demand periods. We find that retailers use a *deep and narrow* pass-through strategy (high pass-through on

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loss-leader products, but small pass-through on regular products) during periods of *regular demand* and *broad and shallow* pass-through strategy (smaller, but similar pass-through on both loss-leader and regular products) during periods of *high demand*. Loss leader products continue to obtain higher pass-through in high demand periods, if the category's high demand period is also a high demand period for other product categories as well.

Keywords Pass-through · Retail competition · Loss leaders · Trade promotions

JEL classifications L11 · L81 · M30

1. Introduction

Trade promotions are the most widely used promotional tool by manufacturers of frequently purchased consumer products. Anderson Consulting (1996) reports that they represent about 60% of marketing expenses. Trade promotions have grown dramatically over the last two decades: from \$8 billion in 1980 to \$85 billion in 2002 (Cannondale Associates, 2002). Yet, manufacturers usually rank the inefficiency of trade deals as their primary concern in surveys. This is because only a fraction of the trade promotions are passed through to consumers. Manufacturers estimate that only 52% of promotions are passed through to consumers, while retailers claim that about 62% are passed through to consumers (Cannondale Associates, 2002).

These average figures of 52% or 62% however reveal only a partial picture of trade deal pass-through, because there is substantial variation in pass-through across different categories and products (e.g., Chevalier and Curhan, 1976; Walters, 1989; Armstrong, 1991). Some products indeed receive high pass-through, while others receive very limited pass-through. In a recent empirical study (Besanko et al., 2005) estimate that pass-through varies as much as 22% in the toothpaste category to as much as 558% in the beer category. They also point out that there is substantial variation in pass-through across products even within a category. It is well recognized that certain "high profile" items are usually treated as loss-leaders by the retailer and therefore receive high pass-through, while other items receive low pass-through (Grier, 2001).

But little attention has been paid to the variations in pass-through over time. For example, in seasonal products does the pass-through of products change in periods of high demand relative to periods of regular demand? Are these relative changes in pass-through different for products that retailers use as loss-leaders compared to regular items? If indeed pass-through is systematically different over different periods, then manufacturer trade promotion dollars are likely to be more or less efficient in certain periods than in others. An understanding of when pass-through rates are likely to be high for different types of products can help manufacturers make trade promotions more efficient. Our objective in this paper is to therefore gain insights into *how pass-through changes over time*.

The issue of whether pass-through changes over time is in general an important one, because sales in many product categories vary substantially during different periods of the year. According to the National Retail Foundation, holiday sales (includes

November and December) account for almost a quarter of the annual total sales. For example, according to the 2002 Annual Benchmark Report for Retail Trade and Food Services of the U.S. Census Bureau, sales of jewels in December were roughly 22.35% of the annual sales in 2001.

Pass-through is usually defined as the "*the proportion of the discounts offered by a manufacturer to a retailer in a trade deal that is transferred to the end consumers as a price reduction*" (for e.g., Grocery Trade Review, 2000). Applying this definition when investigating differences in passthough during high and regular demand periods in a manner that is useful for manufacturers is complicated by the fact that the *price elasticity in high demand periods and low demand periods can be different.* Researchers have found that demand elasticity is greater in high demand periods (Warner and Barsky, 1995; MacDonald, 2000; Sudhir et al., 2005). If indeed, demand elasticity is greater in a high demand period, retail prices will fall no matter whether manufacturers cut wholesale prices or not. Thus a small reduction in wholesale price will appear to "cause" a large retail price reduction, and one may incorrectly conclude that pass-through is extremely high. Such an incorrect interpretation might prompt manufacturers to give much higher price reductions in high demand periods than are warranted. Since a retail price reduction could have been obtained without any trade promotion, the optimal trade promotion would be much smaller than what would be implied by a pass-through analysis that does not take into account the changes in elasticity.

It is therefore critical to "control" for the retail price reduction that will occur even without a trade promotion in order to measure the "true" pass-through for a trade promotion in high demand periods. We therefore estimate a demand model which allows for price elasticities to be different in high and low demand periods. This enables us to compute the optimal within-category retail profit maximizing margin conditional on the demand model. Note that since we do not model the cross category effects within the demand model, this margin will not account for these potential effects that the retailer will account for in setting the retail price. Nevertheless, it allows us to "control" for the potential reduction in retail prices simply due to the change in demand elasticity. Any further retail price reduction beyond what could be attributed purely to the change in demand elasticity is attributed to the effect of the trade promotion and measured as pass-through. We believe that this operationalization of "pass-through" that we introduce in this paper is critical for manufacturers to get an accurate picture of the efficiency of their trade promotion dollar across time.

Given our interest in the effectiveness of trade promotions, we separate the wholesale price into two components: the "regular" wholesale price and trade deal discount. Typically papers on pass-through (e.g., Bulow and Pfleiderer, 1983; Walters, 1989; Tyagi, 1999; Kumar et al., 2001; Besanko et al., 2005) simply combine these into the effective wholesale price. To be consistent with the spirit in which managers interpret pass-through, it is important to separate the regular wholesale price and the trade deal and measure pass-through by estimating how much of the deviation from the regular wholesale price is passed through to the end-consumer. Note that we treat price increases differently from price decreases; this is important because trade deals are typically thought of as price decreases. We illustrate our approach by analyzing two product categories–canned tuna and beer, both of which have well defined periods of high and regular demand.

This paper is related to the paper by Chevalier et al. (2003) who investigate how retailer and manufacturer prices change in high demand periods relative to low demand periods. Chevalier et al. aggregate the data to a category level and work with a weighted price index. This aggregation masks differences in price elasticity between high and low demand periods. By estimating demand at the level of the product, we find significant differences in elasticity between high and low demand periods. Chevalier et al. find that retail pricing is consistent with loss-leader pricing and is not driven much by changes in wholesale prices. The finding is consistent with the intuition that we provided earlier that a small change in wholesale price might be accompanied by a large change in retail price in periods of high demand if demand sensitivity is greater.

Researchers studying pass-through typically do not have access to the actual wholesale price in a given period, but only the accounting value of the current inventory. This is generally considered a limitation to be lived with when measuring pass-through (e.g., Chevalier et al., 2003; Besanko et al., 2005). However it should be noted that researchers also do not have information about retailer inventories when studying pass-through. Forward buying by retailers and residual inventories in a promotional period can also bias pass-through measurement. We show in the paper that when retailer inventories are unobserved (as is typical), the use of actual wholesale prices to measure pass-through can lead to more biased estimates of pass-through than would be obtaining by using the accounting value of retailer inventory in the current period (average acquisition cost). Essentially, the use of inventory adjusted wholesale prices ameliorates potential biases in the estimation of pass-through due to unobserved residual inventories and forward buying by using actual wholesale prices. Thus we provide an argument in support for the use of the accounting value of inventory (a.k.a. average acquisition cost) when measuring pass-through rather than actual wholesale prices when retailer inventory is unobserved.

The paper is organized as follows: Section 2 introduces the empirical model and details on how we measure pass-through. Section 3 discusses the estimation strategy. Section 4 describes the data and the results. Section 5 concludes.

2. Model

2.1. Measuring pass-through

Academic research typically defines pass-through as a ratio of change in retail price to a change in wholesale price in many studies i.e., pass-through $\beta = \frac{dp}{dw}$ (Bulow and Pfleiderer, 1983; Tyagi, 1999; Goldberg, 1995). One could empirically measure this by running a regression of retail prices against wholesale prices (e.g., Besanko et al., 2005). However as discussed earlier, this approach is of limited value in the context of products with seasonal demand, where demand elasticity is known to change between periods of high and regular demand. Retail prices are a function of both demand and costs (wholesale price). Several papers have shown that demand sensitivity falls during periods of high demand relative to periods of regular demand (Warner and Barsky, 1995; Sudhir et al., 2005); therefore retail prices can fall even in the absence of a change in wholesale price in a period of high demand. However when manufacturers cut their wholesale prices in periods of high demand due to the higher elasticity, we may attribute all of the change in retail price to the change in wholesale price and thus obtain a misleading and exaggerated measure of pass-through. Hence it is critical to decompose the change in retail price that is (1) due to the change in demand characteristics and (2) due to the change in wholesale price. Pass-through then is simply the change in retail price attributable to the change in wholesale price.

We use the following empirical strategy. We estimate a demand model which accounts for differences in levels of demand and price sensitivity between regular and high demand periods. We then account for the impact of changes in demand characteristics on retail prices by computing the category profit maximizing margins that would be chosen by the retailer in the regular and high demand periods. By subtracting out this margin and regular wholesale price from the retail price, we are then able to measure the change in retail price due to only change in the wholesale price. We therefore look at the relationship between the Retail Price—Regular Wholesale Price—Category Profit Maximizing Margin and change in wholesale price to measure pass-through. We distinguish between a trade deal (reduction in wholesale price) and an increase in wholesale price in the analysis.

2.2. Demand model

We use a random coefficients logit model of demand because it is parsimonious, while at the same time it allows for flexible cross-elasticities between products. Dominick's (the retail chain whose data we use) practiced "zone pricing" policies, for certain categories, where all stores within a pricing zone have the same prices. We therefore develop the demand model by including zone specific effects, but will ignore zone effects if Dominicks does not use zone pricing in a category. The conditional indirect utility of consumer i for brand j at store s which belongs to zone z at period t is then given by:

$$\begin{aligned} u_{ijzt} &= \gamma_j + \tau_{ij} + x_j(\beta_i^* + \beta_i^{**} H_t) - p_{jzt}(\alpha_i^* + \alpha_i^{**} H_t) \\ &\quad + \xi_{jzt} + I_z\left(\beta_i^z + \beta_i^{zz} H_t\right) + \varepsilon_{ijzt} \end{aligned} \tag{1}$$

where γ_j is the mean preference for brand j, τ_{ij} is consumer i's deviation in preference from the mean preference for brand j, x_j is the k-vector of observable characteristics and marketing variables associated with brand j, P_{jzt} is the price of brand j in zone z, at time t, H_t is a dummy variable indicating the high demand period, ξ_{jzt} are the brand specific unobserved characteristics that vary from week to week, I_z are the zone dummies indicating the pricing zone and ε_{ijzt} follows the standard Gumbell distribution. Note that we allow for different sets of parameters for the high and regular demand periods.

The brand specific unobserved characteristics (ξ_{jzt}) that vary across zones from week to week can be due to factors at the market, zone level, or store level that are not captured in the data. For example, this can be due to coupon availability, varying shelf space positions in the store, merchandizing (other than features/displays which is observed) and any other week to week demand shocks (other than the seasonality which is modeled).

We allow for correlation in individual preferences for different brands τ_{ij} by assuming:

$$\tau_{ij} = \varsigma\vartheta_{ij} + \chi_j e_i, \quad \vartheta_{ij} \sim N(0, 1), \quad e_i \sim N(0, 1) \tag{2}$$

This specification is similar to the one used by Chintagunta (2002). The variance for the brand preference for brand j is given by $\varsigma^2 + \chi_j^2$ whereas the covariance between brand j and k given by $\chi_j\chi_k$.

To simplify notation, we define $\theta_i^* = (\alpha_i^*, \alpha_i^{**}, \beta_i^*, \beta_i^{**}, \beta_i^z, \beta_i^{zz})$ as a column vector containing the individual-specific coefficients (non-brand specific). We further decompose the individual parameters as follows:

$$\theta_i^* = \theta_1 + \mu_i, \tag{3}$$

where θ_1 is the mean of the individual-specific coefficients, and μ_i represents the individual deviations from the mean. The individual deviations μ_i are assumed to be independently normal.

$$\mu_i = \sum \nu_i \quad \text{where } \nu_i \sim N(0, I_{k+1}), \tag{4}$$

where Σ is a scaling matrix, and ν_i represents unobserved individual characteristics. Assuming vector $\theta_2 = (vec(\Sigma), \varsigma, \chi_j)$, combining Eqs. (1) and (3), we have:

$$u_{ijzt} = \delta_{jzt}(x_j, p_{jzt}, \xi_{jzt}, I_z, H_t;\ \theta_1, \gamma_j) + \mu_{ijzt}(x_j, p_{jzt}, I_z, H_t, \upsilon_i;\ \theta_2, \tau_{ij}) + \varepsilon_{ijzt} \tag{5}$$

We assume that consumers maximize utility. Consumer i will purchase one unit of j if for all k's (including the outside good denoted by $j = 0$ and whose utility is normalized to $u_{i0zt} = \varepsilon_{i0zt}$), $k \neq i$ if $u_{ij} > u_{ik}$. We aggregate demand across individuals to the zone level for the analysis. We define the region A_{jzt} as the set of consumer unobservable variables that lead to the purchase of good j. Given population distribution functions of ν and ε, denoted by $P*(\nu)$ and $P*(\varepsilon)$ respectively, and assuming independence between these distributions, the market share of j in zone z at time t is given by:

$$s_{jzt}(x_{zt}, p_{zt}, \delta_{zt};\ \theta_2, \tau_{ij}) = \int_{A_{jzt}} dP^*(\upsilon)dP^*(\varepsilon) \tag{6}$$

2.3. Retailer pass-through equation

As we discussed earlier, our strategy in estimating pass-through requires us to control for differences in category profit maximizing margins during different periods of demand and then see how changes in wholesale prices affect retail prices. It is easy to show that the vector of retailer's category profit maximizing margins for the different brands is given by:

$$mg_{zt} = -\begin{pmatrix} \frac{\partial s_{1zt}}{\partial p_{1zt}} & \frac{\partial s_{2zt}}{\partial p_{1zt}} & \cdots & \frac{\partial s_{Jzt}}{\partial p_{1zt}} \\ \frac{\partial s_{1zt}}{\partial p_{2zt}} & \cdots & \cdots & \frac{\partial s_{Jzt}}{\partial p_{2zt}} \\ \cdot & & & \\ \frac{\partial s_{1zt}}{\partial p_{Jzt}} & \frac{\partial s_{2zt}}{\partial p_{Jzt}} & \cdots & \frac{\partial s_{Jzt}}{\partial p_{Jzt}} \end{pmatrix}^{-1} \begin{pmatrix} s_{1zt} \\ s_{2zt} \\ \cdot \\ \cdot \\ s_{Jzt} \end{pmatrix} \tag{7}$$

To understand how a change in wholesale price affects retail price, we want to isolate the effect of the change in wholesale price on retail price. For this reason we subtract out (1) the regular wholesale price and (2) the category profit maximizing margin at the regular wholesale price from the retail price, thus isolating the retail price change due to the wholesale price change. We then estimate a regression with this difference as the dependent variable against the changes in wholesale prices as well as a number of control variables. Specifically we estimate the following regression equation:

$$p_{zjt} - w_{jzt}^{\text{Reg}} - mg_{jzt}^{\text{Reg}} = \lambda Z + \varphi X + \psi_{zjt} \tag{8}$$

where w_{jzt}^{Reg} represents the regular wholesale price for the brand at time t and mg_{jzt}^{Reg} is the category profit maximization price margin for brand j charged by the retailer in zone z at time t at the regular wholesale price.

We explain the rationale for the control variables in the pricing regression. Even though we control for the effects of zone, manufacturers and features/displays in the demand equation and thus through category profit maximizing margin, a retailer may deviate from the normative category profit maximizing margin on the basis of zones, manufacturers and features/displays. Such deviations may be due to (1) differences in retail competition in the different zones, that we are unable to capture in the demand model (2) differences in clout of different manufacturers which might cause certain manufacturers to negotiate lower/higher prices for their products than what might be warranted from a category profit maximizing price, or (3) due to differences in unobserved side payments such as merchandizing allowances, which can affect the extent to which features and displays are used for different products. We include these variables in Z as a vector of control variables that can potentially affect retail prices and allow for these effects to be different across low and high demand periods.

The key coefficients of interest are the pass-through coefficients associated with X. In X we include the following: two variables indicating the extent of wholesale price increases or decreases (note that we seek to identify any asymmetries in responses to price increases/decreases) and interaction variables that interact the wholesale prices increases/decreases with a dummy variable to denote whether this is a high demand period. Note that price decreases enter the regression with a negative sign, and price increases with a positive sign. Hence the coefficient associated with wholesale prices increases/decreases represent pass-through in regular periods, and the coefficients associated with the interaction variables high demand periods indicate the difference in pass-through relative to regular periods during periods of high demand.

ψ_{zjt} is the error term. A typical structural interpretation of this error term would be that this is due to measurement error in the wholesale prices. However, given that the estimated variance for this error is relatively large, a more plausible interpretation is that this is due to error in retailer price optimization.[1]

3. Estimation

3.1. Estimation procedure

We use a two step estimation procedure to estimate the demand equation and the pricing equation. We use the following estimation procedure first developed by BLP (1995) and refined by Nevo (2000) to estimate the demand model. The demand specification incorporates in the error term the presence of unobserved (by the econometrician) characteristics. However, firms observe these characteristics and take them into account when setting prices. Hence the error term in the demand equation is correlated with price, creating an endogeneity problem. One therefore needs to use instrumental variables to estimate the price coefficient without bias.

Since the error term ξ_j enters the demand equation non-linearly, we need to transform the equation such that the error term enters the estimation equation linearly in order to apply standard instrumental variable estimation methods. The linearization is done by using the contracting mapping procedure outlined in BLP (1995), by solving for δ_{jzt}.

$$\delta_{jzt}^{h+1} = \delta_{jzt}^{h} + \ln(S_{jzt}) - \ln(s_{jzt}(x, p_{zt}, \delta_{.zt}; \theta_2, \tau_{ij})) \tag{9}$$

To avoid computing logarithms, we follow the transformation suggested by Nevo (2000). $D_{jz} = \exp(\delta_{jzt})$. Eq. (9) can be rewritten as

$$D_{jzt}^{h+1} = \frac{D_{jzt}^{h} S_{jzt}}{s_{jzt}(x, p_{zt}, \delta_{.zt}; \theta_2, \tau_{ij})} \tag{10}$$

We iterate this equation until it converges. Then, we compute

$$\xi_{jzt} = \delta_{jzt}(\theta_{2,} \tau_{ij}) - x_{jzt}\theta_1 \tag{11}$$

We use Generalized Method of Moments (GMM) to estimate the demand model. Assuming that the demand side instruments (z^d) are exogenous, and therefore independent of the error term, the moment conditions are $E(z^d\xi) = 0$. Then, the GMM

[1] In our empirical analysis, we found that the variance of the wholesale prices was an order of magnitude smaller than the variance in retail prices and the error term.

estimator, given the moment conditions, is defined as.

$$\min_{\theta} \xi' z^d (z^d \Omega z^d)^{-1} z^{d\prime} \xi \tag{12}$$

where Ω is the standard weighting matrix defined by $E(\xi\xi')$.

This algorithm is circular because the weighting matrix Ω is a function of the estimated parameters θ, and the estimated parameters θ are a function of Ω. We therefore use an iterative procedure in which we assume some initial values for θ, then we compute Ω. With this value of Ω, we use the minimization procedure (Eq. (12)), and repeat the procedure until convergence of θ.

We estimate the retailer pricing equation using linear regression, conditional on the demand equation estimates. We first compute the category profit maximizing margin conditional on the regular wholesale prices and the demand estimates by iteratively solving the system of pricing first order conditions to obtain the margin.

$$mg_{jzt}^{\text{Reg}}\left(w_{jzt}^{\text{Reg}}, s_{jzt}, m_0, s_t^*\right) \tag{13}$$

where, s_t^* represents the partial derivatives of shares as a function of prices. The dependent variable in the OLS regression is:

$$y_{jzt} = p_{zjt} - w_{jzt}^{\text{Reg}} - mg_{jzt}^{\text{Reg}}\left(w_{jzt}^{\text{Reg}}, s_{jzt}, m_0, s_t^*\right) \tag{14}$$

and the regression equation estimated is

$$y_{jzt} = \beta X + \lambda Z_{jzt} + \psi_{jzt} \tag{15}$$

The two stage estimation procedure is convenient in terms of computation because it enables us to evaluate different sets of instruments on the demand estimates without potential contamination from supply-side mis-specifications. The cost however is a loss of efficiency. We estimated the final demand and supply equations simultaneously using Generalized Method of Moments (GMM) as follows to test if our results are robust. The GMM estimation procedure is as follows. Given the demand and supply moment conditions $E(z^d\xi) = 0$ and $E(z^s\psi) = 0$, where $z^s = [X', S']'$. Let $\zeta = (\xi', \psi')'$, θ be the set of parameters to be estimated, and $z = \begin{pmatrix} z^d & 0 \\ 0 & z^s \end{pmatrix}$. Then, the GMM estimator, given the moment conditions, is defined as:

$$\min_{\theta} \zeta' z \left(z \Omega z\right)^{-1} z' \zeta \tag{16}$$

Where Ω is the standard weighting matrix defined by $E(\zeta\zeta')$.[2]

[2] In previous versions of the paper, we used the joint GMM estimation for the supply and demand equations. To address reviewer concerns about the effects of instruments on demand estimates and assess the validity of the endogeneity correction on demand estimates, we estimated the demand and supply models separately. Since the joint estimation results are not substantively different from the two step estimation results, we report only the two-step estimation results in this version of the paper.

3.2. Instrumental variables

To deal with the potential endogeneity of retail prices, we use an instrumental variables estimation approach. For instruments, we need to find variables that are correlated with the price shocks, but are independent of the error term. We follow Chintagunta (2002) in using wholesale prices as instruments for retail prices. The caveats discussed in Chintagunta (2002) also apply to our use of wholesale prices as instruments. Additionally, in our context, one could argue that manufacturers who recognize differences in retail pass-through behavior may allocate their trade allowances for merchandizing and set wholesale prices differently during peak demand periods. To the extent that the effect of such trade allowances is captured by the observed features and displays at the store, we control for these effects in the demand equation and wholesale prices can be valid instruments.

However if advertising levels which are unobserved in our data are different across high and low demand periods, this can be a potential problem as acknowledged in Chintagunta (2002). Tuna is not a highly advertised category; hence this issue is unlikely to be a problem in the context of tuna. But beer is a highly advertised category and we acknowledge that both wholesale and retail prices can be correlated with this unobserved effect.

Another concern is that manufacturers may also respond to week-week variation in chain demand. A key assumption in using wholesale prices as an instrument is that manufacturers may not be as aware of the changes in local demand conditions as the retailer is. However, as stated above, if the change in demand conditions on a week-week basis is related to advertising, the use of wholesale prices as an instrument can be problematic.

Unfortunately we do not have data on advertising and do not have access to other instruments. So we follow other researchers (e.g., Chintagunta, 2002; Chintagunta et al., 2005) in using wholesale prices as an instrument. BLP (1995) consider the average of product characteristics of competing products as instruments. Sudhir (2001) uses a similar average but uses only the characteristics of closely related products in computing the average (i.e., items belonging to the same segment). We estimate models with (1) no endogeneity correction (2) only wholesale prices as instruments and (3) wholesale price and the average wholesale prices of similar products and compare the extent of endogeneity correction using these alternative set of instruments.[3]

4. Empirical analysis

4.1. Data

For measuring pass-through, we need information on wholesale prices as well as retail prices. While retail price information is generally available in most scanner datasets, the Dominicks Finer Foods (DFF) database at the University of Chicago is unique in that it also provides information on wholesale prices.

[3] For tuna we used the price per oz for 12 oz cans, for beer we used the price of bottled beer etc.

4.1.1. Category choice

We select two categories from the Dominicks database for this study: canned tuna and beer. As described in the introduction, these two categories have clear periods of high demand. We use these two categories for our analysis because they have naturally occurring high demand periods every year. Tuna is in high demand during the 40 day period of Lent, when religious Christians do not eat any form of meat. The only meats they are allowed to eat during this period are those of fish and mollusks. Therefore consumers heavily substitute tuna for meat during this time. On the other hand, beer has several peak demand periods over the year especially during holiday weeks: Memorial Day, July 4, Labor Day, Thanksgiving and the two weeks surrounding Christmas and New Year. The Super Bowl week is also a high demand period. These two product categories are different in another important respect. The high demand period for tuna is idiosyncratic to the category and therefore the retailer does not have much potential benefit from cross-category sales. Further, since Christians substitute the low margin tuna category for the higher margin meat products, this high demand period for tuna can lead to potential negative cross-category effects. In contrast, the high demand periods for beer also tend to be high demand periods for a wide range of grocery product categories, especially other food and snacks. Thus the potential for cross-category sales is much higher with beer.

Tuna has two distinct sub-categories of products: Chunky Light and Solid White. According to a top executive of Starkist, that we interviewed for this paper, Chunky Light is one of the cheapest sources of proteins in the market and retailers usually therefore sell it as a “loss-leader.”[4] In contrast, “Solid white” tuna is a premium product because it comes from a less common species of tuna fish: albacore. Albacore tunas do not swim in tight schools like other tuna species and therefore is more costly to capture an equivalent amount (more information about the different tuna species available at www.bumblebee.com). Hence they are typically sold as a regular product. We exclude minor sub-categories such as diet, white chunk, low sodium and prime tunas and low share brands from the analysis. We do not distinguish between water and oil-based tuna because there are no price differences between the two. We restrict our analysis to the most popular 6 oz can category.

In the beer category, we found that the 24 can pack targeted to the “heavy user” segment was promoted as the loss-leader product across the major brands, while the 12 can pack was sold at higher margins. We exclude the 6 packs which have a very small share from the analysis.

4.1.2. Data issues

The DFF database consists of 400 weeks of data in 94 stores in the Chicago area grouped in pricing zones. The pricing zone policy implies that all the stores in a given zone have the same price. The use of pricing zones allows some level of differentiation in the marketing mix between stores with different demograph-

[4] A manager of Starkist confirmed that retailers typically use “Chunky Light” as a loss leader because of its appeal to the price sensitive segment as the cheapest source of protein. Consistent with this, we also found Safeway and Kroger only used “Chunky Light” in their feature inserts.

ics and competitive positions, but keeps the complexity of setting prices manageable. While Dominicks used three pricing zones for the tuna category, they used an umbrella price across all stores in the beer category. Hence our retail pricing model will be at the zone level for tuna and at the chain level for beer.

There are three data issues that we need to resolve: First, trade deal information is not available in the data set and therefore needs to be inferred. The basic idea is to measure deviations of the current wholesale price for each period with respect to a reference wholesale price that represents the "regular wholesale price." We evaluate two alternative methods of inferring regular prices: (1) the average price of the year and (2) the moving average of past prices (a description of the two measurements is included in Appendix A). For the tuna category, similar results are obtained for both criteria. In the beer category, since periods of high demand were never longer than two weeks, it was not possible to compute a moving average and we therefore use only the annual average price for the beer category.

Second, wholesale price is computed based on the accounting value of the current inventory and not on the wholesale price of the product for the current week. Most researchers have treated this as the actual wholesale price in the current week (e.g., Chintagunta, 2002; Chevalier et al., 2003; Besanko et al., 2005). We show in appendix B, that while this is not ideal, given that retailer inventories are unobserved, the use of such an inventory adjusted wholesale prices ameliorates potential biases in the estimation of pass-through due to unobserved residual inventories and forward buying. See Blattberg and Levin (1987) for a model which uses shipment and inventory data in studying effectiveness of trade promotions.

Third, since consumers generally stockpile tuna when there is a deal, inter-temporal measurement issues can be important. Static choice models (as used in this paper) have been shown to infer higher weekly promotion elasiticities in the presence of stockpiling (e.g., Sun et al., 2003) using individual level data. However it is virtually impossible to identify dynamics using aggregate data as in our case. In order to mitigate any issues of stockpiling at the individual level that might affect elasticities, we temporally aggregate the data. Since manufacturers offer deals for the entire 6-week period of Lent, we aggregate the tuna data over 6 week periods and perform the analysis. We also checked the results with aggregation over 3-week periods and the results are similar. Since the stockpiling problem is not as acute for beer, and the peak periods are typically less than two weeks, we analyze the beer category at the weekly level itself.

To obtain the share of outside good, we need an estimate of total potential market size. We compute the total potential market size as follows: In the case of tuna, we assumed that each household member can potentially consume 1 serving per day on 10% of the days. One serving is estimated as two ounces (according to nutrition information on the Starkist (the leading tuna brand label). The potential market (in ounces) is then obtained by multiplying the customer count (the average number of households in each zone) and the percentage of days the consumer consumes canned tuna. For beer, we use a similar procedure starting with the average annual consumption of beer for adults in the U.S. Then we convert that number into the

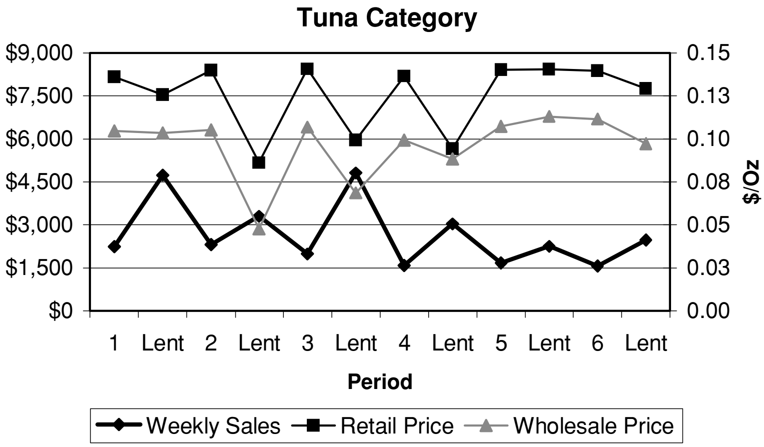

Fig. 1 Average weekly sales, retail and wholesale prices for the tuna category regular periods and lent during the six periods of the data set

weekly consumption of beer in ounces and multiply it by the number of adults that visited the chain in a given week.

4.2. Descriptive analysis

We first provide preliminary descriptive analysis for the two categories that we use in our analysis, before discussing the estimation results.

4.2.1. The tuna category

Figure 1 reports the weekly average of the sales of the tuna category for DFF over six years from September 1989 to May 1995. We aggregate the data into regular weeks and the six weeks of Lent in the figure. The average weekly sales of regular periods are followed by the average weekly sales during Lent. While the average sales doubles during the weeks of Lent, the wholesale and retail prices fall dramatically. Thus contrary to the simple conventional wisdom that prices should rise in periods of high demand, we find a dramatic reduction in average wholesale and retail prices during the high demand periods.

Table 1 summarizes the sales and prices of Chunky Light and Solid White tuna at the brand level. The average sales per week during high demand periods are roughly three times the sales relative to regular periods.

The wholesale and retail prices for Chunky Light decreased during Lent for all brands. However the margin increased for all brands except Starkist. This suggests that the retail prices did not fall as much as wholesale prices for this sub-category. This is particularly surprising, given the results in Chevalier et al. (2003) that the fall in retail prices during high demand periods is much greater on average than the fall in wholesale prices. The proportion of brands sold on promotion increased overall during Lent, but this was not true for all brands.

Table 1 Descriptive statistics – tuna category

	Starkist		Bumble bee		Chicken of the see		Geisha		Heritage house		Total	
	Regular	Lent	Regular	Lent	Regular	Lent	Regular	Lent	Regular	Lent	Regular	Lent
Sales(US$)												
Chunky light	2,972,380	694,299	1,778,494	701,822	1,792,642	940,980			1,259,226	276,623	7,802,743	2,613,723
solid white	700,203	123,916	989,098	174,493	484,909	81,658	887,459	151,092			3,061,669	531,158
Total (US$)	3,672,583	818,215	2,767,591	876,315	2,277,551	1,022,638	887,459	151,092	1,259,226	276,623	10,864,411	3,144,882
Sales (Oz/week)												
Chunky light	92,884	175,667	62,066	186,391	56,531	316,410			44,780	71,371	256,261	749,839
solid white	9,698	12,434	13,730	17,748	7,194	8,493	14,291	17,481			44,912	56,155
Total (US$)	102,581	188,101	75,796	204,139	63,725	324,903	14,291	17,481	44,780	71,371	301,173	805,994
Price (Cnts/Oz)												
Chunky light	12.40	10.98	11.11	10.46	12.29	8.26			10.90	10.77	11.80	9.68
solid white	27.99	27.68	27.92	27.31	26.13	26.71	24.07	24.01			26.42	26.27
Average	13.88	12.08	14.15	11.92	13.85	8.74	24.07	24.01	10.90	10.77	13.98	10.84
Wholesale price (Cs/Oz)												
Chunky light	9.30	8.93	8.76	7.92	9.62	5.87			8.04	7.19	9.02	7.22
solid white	21.04	20.76	20.42	19.34	18.71	19.35	18.08	18.23			19.53	19.31
Average	10.41	9.71	10.87	8.91	10.65	6.23	18.08	18.23	8.04	7.19	10.59	8.06
Margin (%)												
Chunky light	25.04%	18.69%	21.14%	24.31%	21.74%	28.90%			26.24%	33.20%	23.59%	25.41%
solid white	24.83%	25.02%	26.87%	29.17%	28.38%	27.54%	24.89%	24.07%			26.07%	26.50%
Average	25.00%	19.65%	23.19%	25.28%	23.15%	28.79%	24.89%	24.07%	26.24%	33.20%	24.29%	25.59%
Promotion (% of Sales)												
Chunky light	40.98%	40.67%	30.28%	52.57%	52.84%	45.76%			36.03%	42.61%	40.47%	45.91%
Solid white	23.90%	40.01%	35.24%	51.54%	30.92%	59.69%	38.12%	66.09%			32.80%	54.24%
Average	37.72%	40.57%	32.05%	52.37%	48.17%	46.88%	38.12%	66.09%	36.03%	42.61%	38.30%	47.31%

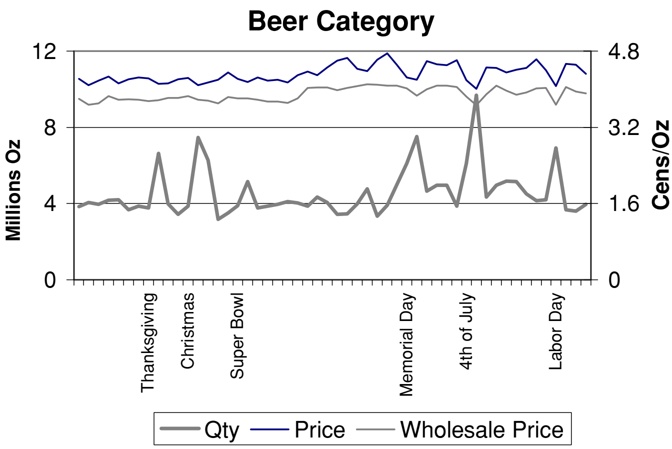

Fig. 2 Average weekly sales, retail and wholesale prices for the beer category 1991–1992

For Solid White tuna, the price changes during Lent had a different characteristic. Retail and wholesale prices changed relatively little on average relative to the regular demand period. However, this does not mean that there were no changes in wholesale prices. In fact we find that during the period of Lent, trade deals were offered more often (31% in Lent, 6.5% in regular periods), but wholesale prices were increased more often as well (13% in Lent, 6.9% in regular periods). Thus the variability in prices was greater during the Lent period. On average, the margins were greater and the proportion of brands sold in promotion dramatically increased.

4.2.2. The beer category

Figure 2 shows the weekly sales of beer for the period 1991–1992. Beer has several peaks of demand during the weeks of special holidays of the year that typically last from one to two weeks. Note that it is critical to our analysis that we recognize that the increases in sales are not merely due to the reduction in prices, but due to a fundamental increase in demand for these products. These high demand periods also have the lowest retail and wholesale prices.

From Table 2, we see that the 24-can beer pack is generally sold as a loss leader with margins very close to zero or even negative. The 12-can pack is sold as a regular product and has higher margins. The high demand weeks (about 10 weeks per year) account for more than 50% of the total sales in the remaining 42 weeks. For both the 12 pack and 24 pack, retail and wholesale prices fall during periods of high demand. But as opposed to the tuna category, the retail margins also fall. Hence it appears that the retailer pass-through is more on average during high demand periods. But we need to control for the effects of changes in demand elasticity, it is not possible to say whether pass-through is indeed greater in high demand periods.

Table 2 Descriptive statistics-beer category

		Miller		Budweiser		Old style		Total	
		Reg	Season	Reg	Season	Reg	Season	Reg	Season
Sales (US$)									
Cans	12-pck	2,543,100	1,252,505	471,079	225,886	438,120	211,796	3,452,300	1,690,186
	24-pck	4,822,426	3,098,335	1,279,424	521,438	2,451,380	1,218,870	8,553,230	4,838,643
	Total US$	7,365,526	4,350,840	1,750,504	747,324	2,889,501	1,430,666	12,005,530	6,528,829
Sales (cans/week)									
Cans	12-pck	27,616	67,334	4,842	11,577	4,636	11,762	37,094	90,673
	24-pck	61,295	198,535	16,481	31,616	34,330	84,174	112,106	314,325
	Total US$	88,912	265,869	21,323	43,192	38,966	95,937	149,201	404,998
Price (Cnts/Oz)									
Cans	12-pck	4.65	4.43	4.91	4.65	4.77	4.29	4.70	4.44
	24-pck	3.97	3.72	3.92	3.93	3.61	3.45	3.85	3.67
	Average	4.18	3.90	4.15	4.12	3.75	3.55	4.06	3.84
Wholesale price (Cs/Oz)									
Cans	12-pck	4.08	4.04	4.11	4.06	4.08	3.62	4.08	3.99
	24-pck	3.90	3.82	3.89	3.85	3.82	3.97	3.88	3.86
	Average	3.96	3.88	3.94	3.90	3.85	3.92	3.93	3.89
Margin (%)									
Cans	12-pck	12.35%	8.80%	16.40%	12.55%	14.48%	15.53%	13.17%	10.14%
	24-pck	1.73%	−2.94%	0.81%	2.06%	−5.89%	−15.02%	−0.59%	−5.44%
	Average	5.40%	0.44%	5.01%	5.23%	−2.80%	−10.49%	3.37%	−1.41%
Promotion (% of Sales)									
Cans	12-pck	43.15%	57.99%	20.11%	38.44%	34.41%	15.48%	38.90%	50.05%
	24-pck	57.33%	91.80%	67.27%	42.34%	68.24%	63.77%	61.94%	79.41%
	Average	52.43%	82.07%	54.58%	41.16%	63.11%	56.62%	55.32%	71.81%

4.3. Estimation results

4.3.1. Demand

We first report and discuss the demand equation estimates for the tuna and beer categories, before the results on retailer pass-through. The demand estimates and elasticity matrix for tuna reported in Tables 3 and 4 respectively. The corresponding tables for beer are in Tables 5 and 6 respectively. As discussed earlier, we control for zonal differences in demand equations for tuna, because tuna prices are set differently for each zone. Since beer prices are common across zones, we estimate the demand and supply equations at the chain level for this category.

We first discuss the tuna results. The first column of Table 3 reports the results without endogeneity correction; the second column reports results using only wholesale prices as instruments; the third column reports the results with both wholesale prices and average wholesale prices of other similar products. We find the greatest price endogeneity correction in the third column; the results are similar on the other variables. We report the first-stage R^2 for the price regression against the instruments and the corresponding F-statistics below each column. The R^2 and F-statistics indicate that the instruments have reasonable explanatory power in explaining the retail prices.

We find that preference for tuna increased in all three zones during the period of Lent as reflected in the zone-Lent interaction variables. The demand for tuna is greatest in zone 2 in the regular period and it also has the greatest increase in demand during the period of Lent. This is perhaps due to the fact that this region has the median level of income among the three zones. Zone 1 consumers have the lowest level of income and therefore consume the least amount of tuna, while Zone 3 consumers with higher income levels perhaps buy more expensive fish rather than tuna. Starkist (which is treated as the base brand) has the highest relative coefficient in the demand equation, consistent with its high market share. There was also significant heterogeneity in preferences for the different brands. We found that the preferences for brands were relatively independent, as reflected in the insignificant estimate of the covariance in preferences across brands.

"Solid White" has a positive coefficient relative to "Chunky Light" as expected, but during Lent this relative preference increases even further indicating that a number of people who shift from other meats to tuna are in fact shifting more to "Solid White." The presence of features and display promotions increased demand for the category during regular periods. Even though feature and display has a negative and significant coefficient, the net effect during Lent is not significantly different from zero.[5] Consumers who now actively search for good prices do not need features or displays as much to get their attention to the price cut.

The price coefficient is significantly negative as expected. Further price sensitivity increases during the period of Lent. This is also reflected in the average elasticity matrices for regular periods and Lent reported in Table 4(a) and (b) respectively.

[5] We estimated the model with Feature*(1-Lent) and Feature*Lent and find the Feature*Lent is not significantly different from zero.

Table 3 Demand parameters–tuna

	No instruments				Wholesale price				Wholesale price and average wholesale prices of similar products			
	Mean		Std dev		Mean		Std dev		Mean		Std dev	
Zone 1	−2.669***	(0.045)	0.056	(1.655)	−2.659***	(0.045)	0.056	(2.434)	−2.405***	(0.046)	0.054	(1.389)
Zone 2	−0.215***	(0.047)	0.015	(0.644)	−0.188***	(0.047)	0.015	(0.979)	0.170***	(0.048)	0.015	(0.687)
Zone 3	−0.899***	(110.043)	0.102	(1.793)	−0.881***	(0.044)	0.101	(2.829)	−0.557***	(0.044)	0.099	(1.999)
Zone 1 × Lent	1.476***	(0.437)	–		2.591***	(0.634)	–		2.262***	(0.607)	–	
Zone 2 × Lent	2.707***	(0.510)	–		3.863***	(0.706)	–		3.597***	(0.679)	–	
Zone 3 × Lent	1.821***	(0.477)	–		3.043***	(0.678)	–		2.705***	(0.650)	–	
Bumble bee	−0.230***	(0.046)	0.616**	(0.307)	−0.240***	(0.046)	0.634	(0.463)	−0.236***	(0.047)	0.615*	(0.339)
C.O.S	−0.418***	(0.041)	0.011	(0.254)	−0.429***	(0.043)	0.011	(0.308)	−0.430***	(0.044)	0.011	(0.283)
Geisha	−0.470***	(0.044)	1.020***	(0.229)	−0.482***	(0.048)	1.003***	(0.338)	−0.463***	(0.048)	1.009***	(0.230)
Heritage house	−0.973***	(0.071)	0.785***	(0.195)	−0.986***	(0.072)	0.808***	(0.272)	−0.961***	(0.073)	0.759***	(0.196)
Brand covariance	–		−0.135	(0.194)	–		−0.138	(0.235)	–		−0.129	(0.228)
Solid white	−0.025	(0.036)	–		−0.035	(0.037)	–		0.111***	(0.037)	–	
Solid white × Lent	0.872	(0.690)	–		2.586***	(0.935)	–		2.162**	(0.892)	–	
Feature/Display	0.309***	(0.049)	0.047	(0.775)	0.316***	(0.049)	0.046	(0.815)	0.288***	(0.050)	0.046	(0.857)
Feature/Display × Lent	−0.556 *	(0.287)	–		−0.703**	(0.315)	–		−0.640**	(0.317)	–	
Price	−2.416***	(0.251)	1.176***	(0.154)	−2.453***	(0.383)	1.210***	(0.225)	−2.825***	(0.291)	1.391***	(0.176)
Price × Lent	−0.699*	(0.400)	–		−1.755***	(0.562)	–		−1.463***	(0.535)	–	
First stage R^2 (price against instruments)					0.94				0.95			
F-stat					19137				10768			
GMM Objective	$1.32e-7$				$4.83e-5$				3.808			

Table 4 Elasticity matrix in regular periods and during lent: Tuna

	Chunky light				Solid white			
	Starkist	B Bee	C.O.S	HH	Starkist	B Bee	C.O.S	Geisha
(a) In regular periods								
Chunky light								
Starkist	−3.048	0.171	0.145	0.149	0.159	0.170	0.171	0.155
Bumble bee	0.026	−1.977	0.022	0.041	0.025	0.043	0.032	0.020
C.O.S	0.135	0.131	−3.086	0.185	0.136	0.133	0.105	0.138
Heritage house	0.019	0.035	0.027	−1.750	0.019	0.035	0.019	0.013
Solid white								
Starkist	0.105	0.110	0.097	0.098	−3.121	0.109	0.112	0.100
Bumble bee	0.018	0.029	0.016	0.028	0.018	−1.967	0.022	0.014
C.O.S	0.032	0.040	0.022	0.028	0.032	0.039	−2.407	0.040
Geisha	0.087	0.073	0.083	0.057	0.085	0.072	0.119	−3.335
(b) During lent								
Chunky light								
Starkist	−4.398	0.536	0.511	0.469	0.547	0.536	0.530	0.515
Bumble bee	0.036	−3.161	0.030	0.071	0.031	0.073	0.050	0.028
C.O.S	0.393	0.342	−4.073	0.488	0.395	0.348	0.289	0.371
Heritage house	0.026	0.058	0.036	−3.020	0.023	0.058	0.031	0.018
Solid white								
Starkist	0.657	0.497	0.650	0.445	−4.218	0.498	0.544	0.632
Bumble bee	0.027	0.055	0.024	0.055	0.025	−3.424	0.038	0.020
C.O.S	0.063	0.091	0.045	0.070	0.058	0.090	−3.482	0.072
Geisha	0.289	0.231	0.273	0.187	0.282	0.231	0.331	−4.977

Table 5 Demand parameters–beer

	No instruments		Wholesale price and average wholesale prices of similar products	
	Mean	Std Dev	Mean	Std Dev
Miller	−5.066*** (0.116)	1.209 (1.201)	5.302*** (0.201)	1.073 (0.962)
Budweiser	−8.697*** (0.080)	2.084 (1.341)	1.975*** (0.145)	1.630 (1.722)
Old style	−6.772*** (0.094)	0.892 (0.809)	3.309*** (0.085)	0.873 (1.408)
Brand covariance	–	2.303 (1.651)	–	2.625** (1.060)
Holiday	10.645*** (2.700)	1.241 (0.965)	23.056*** (8.410)	1.103* (0.627)
Lite	−0.837*** (0.100)	0.692 (0.615)	−0.756*** (0.085)	0.710 (0.796)
Lite × Holiday	−0.181 (0.330)	1.822 (1.174)	−0.078 (0.286)	1.566* (0.849)
24 pack	0.185* (0.108)	1.617*** (0.319)	−0.762** (0.342)	1.553 (1.221)
24 pack × Holiday	−2.056*** (0.650)	–	−4.034** (1.612)	–
Feature/Display	18.527*** (0.826)	0.487 (1.690)	6.826 (4.153)	0.472 (5.492)
Feature/Disp × Holiday	0.360 (2.716)	–	−0.064 (10.306)	–
Price	−0.358 (0.707)	0.460 (0.699)	−2.509*** (0.225)	0.499* (0.268)
Price × Holiday	−2.216*** (0.533)	0.306 (0.206)	−4.701*** (1.692)	0.296* (0.166)
Feature/Display × Price	−7.550*** (0.204)	4.001*** (0.554)	−3.995*** (1.004)	3.131*** (0.585)
Feature/Display × Price × Holiday	0.537 (0.669)	–	0.049 (2.505)	–
First stage R^2 (price against instruments)			0.53	
F-Stat			886	
GMM objective	$4.85E-18$		$4.6e-009$	

Table 6 Elasticity matrix in regular periods and peak periods: Beer

	12-Can						12-Can					
	Miller	Miller L	Bud	Bud L	OS	OS L	Miller	Miller L	Bud	Bud L	OS	OS L
(a) In regular periods	12 Can											
Miller	−1.373	0.168	0.199	0.170	0.024	0.076	0.018	0.056	0.047	0.091	0.059	0.109
Miller Light	0.260	−1.332	0.174	0.834	0.034	0.113	0.025	0.079	0.045	0.108	0.043	0.133
Budweiser (Bud)	0.130	0.055	−1.871	0.063	0.008	0.023	0.008	0.017	0.013	0.030	0.019	0.039
Bud light	0.121	0.392	0.102	−1.842	0.015	0.046	0.012	0.034	0.022	0.059	0.026	0.085
Old style (OS)	0.007	0.006	0.004	0.005	−2.137	0.061	0.206	0.082	0.013	0.012	0.016	0.019
OS Light	0.019	0.021	0.012	0.018	0.170	−1.714	0.179	0.604	0.034	0.023	0.043	0.040
24 Can												
Miller	0.003	0.002	0.002	0.002	0.130	0.042	−2.279	0.061	0.008	0.008	0.010	0.012
Miller light	0.008	0.008	0.006	0.007	0.095	0.347	0.106	−2.188	0.019	0.016	0.025	0.026
Budweiser (Bud)	0.018	0.011	0.008	0.011	0.023	0.014	0.023	0.017	−1.804	0.024	0.122	0.034
Bud light	0.033	0.030	0.021	0.031	0.072	0.026	0.075	0.032	0.096	−1.492	0.090	0.164
Old style (OS)	0.011	0.005	0.005	0.006	0.010	0.009	0.011	0.012	0.057	0.012	−1.809	0.018
OS Light	0.022	0.026	0.018	0.031	0.094	0.046	0.098	0.050	0.108	0.116	0.087	−1.863
(b) In peak periods	12 Can											
Miller	−4.486	1.338	0.553	0.849	0.371	0.591	0.296	0.361	0.458	0.314	0.433	0.308
Miller Light	0.813	−4.508	0.292	1.633	0.169	0.365	0.078	0.161	0.173	0.432	0.153	0.432
Budweiser (Bud)	0.728	0.352	−4.378	0.708	0.114	0.388	0.472	0.468	0.114	0.158	0.504	0.223
Bud light	0.295	1.026	0.429	−5.049	0.058	0.126	0.076	0.139	0.078	0.225	0.134	0.472
Old style (OS)	0.107	0.074	0.025	0.023	−5.997	0.207	0.930	0.361	0.099	0.150	0.063	0.070
OS Light	0.048	0.068	0.027	0.033	0.964	−4.543	0.281	1.649	0.105	0.075	0.047	0.057
24 Can												
Miller	0.038	0.016	0.026	0.015	0.645	0.173	−6.001	0.396	0.029	0.032	0.052	0.046
Miller light	0.028	0.023	0.040	0.028	0.251	0.846	0.219	−6.143	0.074	0.032	0.061	0.050
Budweiser (Bud)	0.233	0.128	0.159	0.041	0.284	0.263	0.257	0.314	−5.771	0.439	0.521	0.180
Bud light	0.240	0.259	0.086	0.216	0.650	0.252	0.357	0.255	0.696	−5.552	0.443	1.133
Old Style (OS)	0.049	0.022	0.076	0.054	0.004	0.081	0.022	0.105	0.127	0.031	−6.196	0.071
OS Light	0.215	0.296	0.343	0.757	0.596	0.337	0.542	0.453	0.393	0.987	0.652	−5.698

The average elasticity for Lent increased by about 50% compared for regular periods.

The beer results are reported in Table 5. The first column reports the results without endogeneity correction. The second column report the results with endogeneity correction using own wholesale prices and prices of other brands.[6] We see a distinct endogeneity correction in the price coefficient upon performing the endogeneity correction. The preference for beer increased during holidays as expected by the increased demand during these periods. Reflecting the niche nature of "Lite" products, we find that there is a significant mean negative coefficient for "Lite." As expected, feature and display promotions increased demand for the products and its effects did not change during the high demand periods.

Price coefficient is significantly negative as with the tuna category, and the price sensitivity increased during the holidays. This is also reflected in the average elasticity matrices for regular periods and holidays reported in Table 6(a) and (b) respectively. In fact the increase in price elasticity was substantially higher (around 200% on average) for a discretionary product like beer than for tuna, which at the category level became much more of necessity during the period of Lent for Christian consumers. So the increase in price sensitivity for Lent must have come from increased price search across stores by consumers buying large quantities, whereas the increase in price sensitivity for beer might be due to category expansion to the more price sensitive customers as well as due to increased price search.

It is particularly important that we find that the price sensitivity is greater in high demand periods consistent with the theoretical claim of Warner and Barsky (1995) and the empirical results reported in MacDonald (2000) and Sudhir et al. (2005). As discussed earlier, it makes it critical that we consider the effect of changes in demand elasticity on retail prices independent of changes in wholesale prices. Not accounting for this effect will cause us to mis-estimate the level of retail pass-through in the market.

Interestingly, Chevalier et al. (2003) find that there are no differences in elasticity between high and low demand periods using the same data. However, the key difference between our analysis and theirs is that our analysis is at a disaggregate level, while they used an aggregate category level demand and a share-weighted price in estimating the demand. We also find that an analysis of aggregate demand leads to no differences in elasticities between high and low demand periods, suggesting that the aggregation masks differences in elasticity because it averages out price changes across brands. Our results based on disaggregate data is able to disentangle the differential impact of price changes across different brands and thus identify the change in price elasticity.

4.3.2. Retailer pricing

We present the estimates of the retailer pricing equation in Tables 7 (for the tuna category) and 8 (for the beer category). We first discuss the results for the tuna category.

[6] The model with only wholesale prices as instruments did not converge for the beer category.

Table 7 Retailer pricing-Tuna

		Model 1		Model 2	
Pass through-chunky light	WP Increase	−0.270	(0.354)	−0.238	(0.338)
	WP Decrease	1.720***	(0.235)	1.769***	(0.224)
	WP Increase × Lent	0.891	(0.558)	0.659	(0.538)
	WP Decrease × Lent	−0.905***	(0.261)	−0.929***	(0.251)
Pass through -solid white	WP Increase	0.079	(0.201)	−0.048	(0.192)
	WP Decrease	0.129	(0.204)	0.006	(0.195)
	WP Increase × Lent	0.519	(0.507)	0.782	(0.493)
	WP Decrease × Lent	1.027**	(0.401)	1.134***	(0.382)
Zone chunky light	Zone 1	−0.375***	(0.015)	−0.403***	(0.017)
	Zone 2	−0.431***	(0.016)	−0.460***	(0.018)
	Zone 3	−0.321***	(0.017)	−0.349***	(0.018)
	Zone 1 × Lent	0.107**	(0.044)	0.084*	(0.048)
	Zone 2 × Lent	−0.273***	(0.046)	−0.294***	(0.050)
	Zone 3 × Lent	−0.036	(0.047)	−0.058	(0.050)
Zone solid white	Zone 1	−0.412***	(0.014)	−0.456***	(0.016)
	Zone 2	−0.627***	(0.015)	−0.671***	(0.016)
	Zone 3	−0.419***	(0.015)	−0.463***	(0.016)
	Zone 1 × Lent	0.419***	(0.063)	0.422***	(0.066)
	Zone 2 × Lent	−0.017	(0.067)	−0.013	(0.069)
	Zone 3 × Lent	0.297***	(0.068)	0.300***	(0.070)
Feature display	Chunky light	−0.177***	(0.028)	−0.175***	(0.027)
	Chunky light × Lent	0.067	(0.072)	0.045	(0.070)
	Solid white	−0.131***	(0.025)	−0.151***	(0.024)
	Solid W × Lent	0.007	(0.092)	0.015	(0.089)
Mfr dummies and lent interactions included		No		Yes	

For tuna, we report two sets of results: one without manufacturer effects and one with manufacturer effects.[7] The most interesting results for our purposes are the impact of trade promotions (or wholesale price decreases) and these pass-through effects are robust across the specifications. We will discuss the results based on Model 2 which includes manufacturer effects further.

The pass-through for price decreases is 177% for Chunky Light, but not significantly different from zero for Solid White Tuna in regular periods. Thus the pass-through for a loss-leader is substantially higher than for products sold as a regular product. However, during the period of Lent, the retailer cuts down on pass-through for the Loss leader product to about 84%. In contrast the pass-through for solid white tuna goes up to 114%. Thus *during high demand periods, both products receive approximately equal pass-through of about 100% where all of the reductions in wholesale*

[7] The manufacturer effects include manufacturer dummies and manufacturer-lent interaction effects. Note that potential cross pass-through effects are already accounted for in the category profit maximizing margin. Based on a reviewer's suggestion, we checked if our results are robust to including wholesale prices of other brands (i.e., cross-pass-through effects). The inclusion of the cross-wholesale price increases the number of estimated coefficients and therefore the zone effects became insignificant in this specification. However the substantive insights about pass-through effects continue to be similar. Since we did not find store traffic effects to be significant in the tuna category, we have not included these in the reported regressions; we however report the effects for beer.

Table 8 Retailer pricing-beer

		Model 1		Model 2		Model 3	
Pass through-24 can	WP Increase	−0.053	(0.299)	0.027	(0.284)	0.013	(0.284)
	WP Decrease	2.107***	(0.312)	1.900***	(0.297)	1.888***	(0.297)
	WP Increase × Holiday	0.805	(0.599)	0.437	(0.573)	0.449	(0.573)
	WP Decrease × Holiday	−0.680	(0.599)	−0.240	(0.571)	−0.216	(0.571)
Pass through -12 can	WP Increase	0.404	(0.807)	0.075	(0.773)	0.068	(0.773)
	WP Decrease	−0.231	(0.443)	−0.299	(0.422)	−0.331	(0.423)
	WP Increase × Holiday	2.538	(1.796)	2.212	(1.739)	2.007	(1.746)
	WP Decrease × Holiday	0.385	(0.681)	1.071	(0.662)	1.093*	(0.662)
Feature display	24-Can Pack	−2.501***	(0.054)	−2.440***	(0.053)	−2.439***	(0.053)
	24-Can Pack × Holiday	1.037***	(0.115)	0.594***	(0.135)	0.595***	(0.135)
	12-Can Pack	−2.728***	(0.080)	−2.531***	(0.078)	−2.528***	(0.078)
	12-Can Pack × Holiday	1.365***	(0.168)	0.798***	(0.180)	0.793***	(0.180)
Proxy for competition	Store traffic	−0.099***	(0.010)	0.339**	(0.145)	0.495***	(0.187)
	Store traffic × Lent					−0.391	(0.297)
Mfr dummies and holiday interactions included		No		Yes		Yes	

prices are passed on to the consumer. But *during regular demand periods, the retailer virtually does not pass-through any discounts for Solid White, but amplifies any trade promotion and almost doubles the discount offered by the manufacturer to the retailer for Chunky Light*. The pass-through for price increases are not significantly different from zero.

We also estimate multiple specifications of the pricing equation for beer. Given no difference in prices across zones, we do not estimate zone effects for beer. But we include store traffic as an additional control variable in the estimation. Model 1 does not include manufacturer effects, while Model 2 includes manufacturer effects. In addition, Model 3 checks if store traffic effects are different across regular and high demand periods. As with tuna, the impact of trade promotions (or wholesale price decreases) and the pass-through effects which are the focus of the paper are robust across specifications. However, not including manufacturer fixed effects appears to significantly bias feature/display and store traffic coefficients, suggesting that there are systematic differences in how different manufacturers used features/display or respond to periods of store traffic. We further discuss the results of Model 3.

The pass-through for wholesale price decreases is 189% for the loss leader 24 can pack, but insignificantly different from zero for the 12 oz pack in regular periods. Thus the pass-through for a loss-leader is substantially higher than for products sold as a regular product. However, during the peak holiday period, the pass-through for 12 can pack goes up to about 109% (this effect is only marginally significant at $p < 0.1$), which is very similar to the number for tuna during peak periods. The only difference we observe is for the loss-leader product in the beer category. Here we do not find a significant change in pass-through for the high demand period, though we note that the coefficient is negative (similar to tuna). As with tuna, an increase in wholesale price during regular periods is not passed through by the retailer, resulting in an insignificant coefficient for both the 12 and 24 can packs.

The results here are different from Besanko et al. (2005), who state that they did not find any significant differences in pass-through between regular and high demand periods and therefore report only the average pass-through rates. One possible reason is that they used data for only one year (52 weeks) and therefore did not have enough high demand periods in their data. We have data for 400 weeks (nearly eight years) and this helps us to identify the differences in pass-through between high and low demand periods. Future work seeking to identify differences between high and low demand periods should use long time-series that encompass a reasonable number of high demand periods in order to detect statistically significant differences.

Further, our analysis shows that it is important to distinguish between wholesale price increases and decreases. Our results suggest that retailers do not pass through wholesale price increases as much as they do price decreases. If this asymmetry is not taken into account and one uses the net price (as in Besanko et al., 2005), we will downward bias the average pass through for price decreases (i.e., trade deal).

5. Discussion

Our pass-through results indicate an interesting dichotomy. During regular demand periods, only the loss-leader products receive a high pass-through for trade promotions. During high demand periods, both loss leader and regular products receive pass-through. Thus one might argue that pass-through is "narrow" i.e., limited to loss-leader products which drive store traffic, while in high demand periods, pass-through is "broad", i.e., extends to both loss-leader and regular products. Thus retail prices are highly responsive to wholesale price discounts in high demand periods, because of the increased price sensitivity of consumers during this period. This effect is general across the two categories we investigated.

A second effect we notice is that loss-leader pass-through fell during the high demand period for tuna, but pass-through did not fall for the loss-leader in the beer category. What might be the cause of this difference? An explanation can be found in the nature of the peak demand period described by Chevalier et al. (2003). They argue that tuna's peak demand is idiosyncratic to the category, i.e., its peak sales does not correspond to peak sales of other categories. In fact, peak tuna sales might be accompanied by decline in sales in such high margin categories such as meats. In contrast, beer's peak demand is a general high demand period, i.e., it is accompanied by higher sales for several other snack categories. Hence the loss-leader nature of beer continues to be highly effective in its peak demand period, because the increased store traffic, will result in higher margins in other categories. This explains why pass-through does not fall for the beer loss-leader. In contrast, for tuna which has an idiosyncratic peak, the loss-leader effect of tuna is moderated by the loss in profits from other categories due to the substitution of other product categories. Hence during the high demand period, the retailer reduces the pass-through for the loss-leader product, by just passing through whatever wholesale price discount it obtains, but not double this discount as it does during regular periods.

In sum, we see evidence of a “narrow but deep” pass-through strategy during regular demand periods. In high demand periods, we see a “broad but shallow” pass-through strategy. The extent of the shallowness depends on whether the increase in demand for a category in the peak demand period is accompanied by increase in demand for other categories as well or not.

6. Conclusion

Many products are highly seasonal and therefore exhibit significant variation in demand over different periods. In this paper, we introduced the argument that pass-through measurement needs to account for differences in levels of demand in order to provide managerially meaningful estimates and interpretation. We therefore investigated how retail pass-through changes during periods of high demand for different sub-categories of products. We recognize that retail prices can fall simply due to changes in price elasticity without any change in wholesale price and therefore it is necessary to control for these differences to meaningfully estimate pass-through. We find that there are substantial differences in pass-through across products that are considered as loss-leaders relative to regular products; further the pass-through differences are different depending on seasonality.

In regular periods, only products that are perceived as loss-leaders (or help drive store traffic) by the retailer receive high pass-through. Hence these brand manufacturers should offer trade promotions more often on their loss-leader products relative to regular products during high demand periods. Trade promotion dollars are very effective during this period, because retailers amplify the discount to the retailer. In the two categories we study, passthrough for the loss-leaders was as high as 177% and 189%. But in high demand periods, manufacturers are in general likely to obtain reasonable pass-through on both regular and loss-leader products, hence it makes sense to provide trade promotions for regular products only during high demand products. But the passthrough for the loss-leader product falls down to 84% and 167% from 177% and 189%. Thus we claim that for products with idiosyncratic peaks in demand, retailers follow a narrow but deep pass-through strategy for regular demand periods, but a broad and shallow pass-through strategy for high demand periods. Product categories which have sales peaks that are coincident with other categories, will also find a broadening of pass-through; however their loss leaders continue to maintain their high pass-through in high demand periods.

In sum, we learnt that it is critical to account for changes in price sensitivity during the high demand periods. Otherwise, we may overestimate the benefits of trade promotions. We find that pass-through changes differently for different categories of products during different periods. Hence an understanding of retailer objectives for a category can aid in understanding how its pass-through will change during different periods.

Current research on pass-through, which estimates an average level of pass-through over the entire year, may seriously underestimate pass-through in certain periods, while they overestimate it during other periods. For example, our results suggest that products either get high pass-through or not depending on whether it is a regular period or high demand period. A measurement technique which does not account for differences in pass-through during different demand periods will obtain an intermediate estimate of pass-through. Our research offers insights on when trade promotions are likely to be effective for different categories of products, thus making trade promotions more effective overall.

Further, our analysis shows that it is important to distinguish between wholesale price increases and decreases. In earlier pass-through research (e.g., Besanko et al., 2005), the net price is used in the analysis. Our results suggest that retailers do not pass through wholesale price increases, but pass through price decreases. If this asymmetry is not taken into account, we will downward bias the average pass-through for price decreases (which is of critical interest to manufacturers offering trade promotions).

6.1. Limitations and future research

Our research and findings are based on one retailer. Data on wholesale prices are hard to obtain, so performing this analysis is hard from an academic research point of view, by replicating across multiple retailers. Nevertheless, it would be useful if these results are validated across other retailers an in other categories in future research.

Our analysis of two categories allowed us to find consistency in the results along multiple dimensions. However one major difference is that while for beer, loss-leader products continued to obtain amplified pass-through (close to double the trade discount was offered to consumers) in high demand periods, we found that pass-through went down for loss-leader products in the tuna category. We explained this difference on the basis of the idiosyncratic increase in sales in tuna during peak demand, while sales peaks for beer were accompanied by higher sales in other product categories as well. It would be worthwhile in future research to replicate these findings in other categories.

In future research, it would be best if we can obtain more precise measures of regular wholesale prices and trade promotions as well as greater detail regarding the forward buying activities of the retailer to more accurately measure pass-through. Even though the smoothed measure of wholesale prices helps us obtain reasonable measures of pass-through even in the presence of stockpiling and unobserved inventories, it would be best if we had the data on these so as to investigate more precisely the impact of forward buying and stockpiling activities on the impact of trade promotions.

7. Appendix A: Inference of trade deals

One limitation of the DFF's data set is that it does not include trade deal information. Trade deals or trade promotions can take different forms: off-invoice allowances, bill-back allowances, flat allowances, free goods, display allowances, free goods, display allowances, and inventory financing (Kumar et al., 2001). However given that we have information on wholesale price; a great part of these promotions can be inferred from the data by detecting temporary significant reductions in the wholesale price. This method of inference implies that we restrict our study of trade promotions to only wholesale price discounts. Fortunately, according to some researchers (Blattberg and Neslin, 1990; Hess et al., 1995) more than 90% of trade promotions involve off-invoice allowances.

The idea behind the inference of trade deals is simple: We compare the wholesale price in a week against a "regular price", which is also inferred based on some average price over a longer period of time. When the measured price decreases a substantial amount below the regular price we infer that there was a trade promotion.

First how does one infer "the regular price"? We used two alternatives: (1) the average price over one calendar year and (2) a moving average of past prices. For tuna, we obtained similar inferences of trade promotion periods using both measures. For the beer category, it was not possible to compute a moving average since the holiday periods are very short (2 weeks), that the trade promotion discount substantially affected the moving average and thus was unable to serve as a reasonable proxy for regular prices. We now discuss how we infer whether there is a trade promotion during a particular period using the two alternative definitions of "regular price."

(1) *Regular price is the average price of the year*: As discussed, we compute the regular price as the average price during the year. We also compute the standard deviation of prices for each year. Assuming a normal distribution for prices, we then classify a period as having a trade promotion if the deviation from the regular price was 1.645 times the standard deviation. This implied that there exists more than a 90% probability that there is indeed a substantially different deviation from the regular price. We also tested other levels of probability in determining trade promotions (95%; 85%) and our reported results are robust.
(2) *Regular price is moving average price*: In this case, we computed the regular prices as a moving average of the wholesale price for each period. The moving average is defined as:

$$w_{rt} = \alpha w_t + (1 - \alpha) w_{rt} - 1$$

The notion is that the retailer updates the reference (or regular price) for each period. We tested the robustness of the results for different values of α. We then classified each period as a trade promotion period if the price deviates from the regular price by more than a threshold value (which is a certain percentage of the regular price). We tested the robustness of the threshold by varying the percentage from 5% to 12.5% of regular price.

8. Appendix B: Measuring pass-through in the presence of residual retailer inventory and forward buying

In measuring pass-through, the literature typically assumes that all the products sold by the retailer in a given period are purchased entirely at the wholesale price negotiated for that period. However this seldom happens in the real world. Retailers may have in stock, products purchased in earlier periods at different prices—residual inventory, or retailers may also take advantage of a trade promotion today to sell in future periods—forward buying. To capture the actual pass through of trade deals, one should correct for the effects introduced by both the residual inventory and the forward buying.

This requires information on what share of stock was acquired at each price. This information is rarely available to researchers and typically not readily available even to retailers, who maintain the accounting values of their inventory using rules such as LIFO or FIFO.

Dominick's measurement of wholesale prices follows such a smoothing procedure. The Average acquisition cost (AAC) is measured as:

$$AAC_t = \frac{n_t^p \cdot w_t + I_{t-1}^f \cdot AAC_{t-1}}{n_t^p + I_{t-1}^f} \tag{A.1}$$

n_t^p: purchase at time t; w_t: wholesale price at time t; I_t^f: inventory at the final of time t.

The AAC represents a weighted average of the present wholesale price and the previous period's AAC. The consensus in the extant literature is that the absence of actual wholesale price information biases the estimates of pass-through. We show that using AAC (rather than the actual wholesale price) for pass-through measurement can help reduce the potential bias in estimating pass-through due to residual inventory and forward buying effects, when inventories are unobserved using two special cases.

1. *Residual inventory.* Assume that in period t there is a residual inventory of I_{t-1}^f. If during this period, a trade deal is offered at a discount (Δw) from the regular wholesale price and the retailer purchases n_1^p units. Suppose the retailer sell all units ($I_{t-1}^f + n_i^p$) to the end consumers at a reduced retail discount of price Δp. The actual measure of pass through for period t that we are interested in is the one measuring the proportion of the trade deal to the retailer that is passed through to the end consumers or:

$$\beta_t = \frac{\text{total deal to consumers}}{\text{total deal to retailer}} = \frac{\Delta p_t \left(n_t^p + I_{t-1}^f\right)}{\Delta w_t n_t^p} \tag{A.2}$$

   Suppose we don't have information on inventory or purchased quantities, but we observe the actual trade deal discount ($\Delta w_t = w_{\text{Reg}} - w_t$). A measure of pass-through in period t that is commonly used is the ratio of change in retail price to change in wholesale prices:

$$\beta_t = \frac{\Delta p_t}{\Delta w_t} \tag{A.3}$$

   Comparing (A.3) with (A.2), we see that (A.3) consistently underestimates the actual value of the pass through. Therefore even if wholesale prices were available but not inventories, this measurement is not adequate for measuring the pass through.
   We show that using AAC's, available in our data, we can get a more accurate measure of pass through.

With AAC, rather than actual wholesale price, the pass-through in period t is:

$$\beta_t = \frac{\Delta p_t}{\Delta AAC_t} \tag{A.4}$$

Let AAC_t be the average acquisition cost in period t. From (A.1), the deviation in average acquisition cost of period t from the regular acquisition price (AAC_{Reg}) is given by:

$$\Delta AAC_t = AAC_{\text{Reg}} - AAC_t = \frac{n_t^p (AAC_{\text{Reg}} - w_t)}{n_t^p + I_{t-1}^f} \tag{A.5}$$

Substituting (A.5) in (A.4) we get:

$$\beta = \frac{\Delta p \cdot \left(n_t^p + I_{t-1}^f\right)}{n_t^p (AAC_{\text{Reg}} - w_t)}. \tag{A.6}$$

Since $AAC_{\text{Reg}} \cong w_{\text{Reg}}$, i.e., the average regular acquisition cost of inventory should roughly equal the regular wholesale price in the long run, Eq. (A).6 (and therefore A.4) gives a measure of pass-through which is roughly equal to the true pass-through in (A.2). It is especially important to note that (A.4) will be a less biased measurement of the pass through, compared to (A.3) which consistently underestimates pass-through (even though it is based on the actual wholesale price in a given period).

2. *Forward buying*. Consider the case in which the retailer forward buys products to be sold one period ahead. In this case we need to relax in Eq. (A.2) the assumption that the entire inventory is sold at time t. Instead consider the case when only n_t^s where ($n_t^s < n_t^p + I_{t-1}^f$) units will be sold in that period.
To focus purely on forward buying in a period assume: (1) that there is no inventory from the previous period or $I_{t-1}^f = 0$, (this also implies $n_t^s < n_t^p$); (2) that the wholesale price in period $t + 1$ is not discounted, i.e., w_{t+1} is the regular price; (3) that the retailer sells the remaining inventory $n_t^p - n_t^s$ in period $t + 1$, and makes no new purchases in period $t + 1$. The true average measure of pass through for period t should consider sales over both periods and is given by:

$$\beta_t = \frac{\Delta p_t n_t^s + \Delta p_{t+1} \left(n_t^p - n_t^s\right)}{\Delta w_t \cdot n_t^p} \tag{A.7}$$

Suppose we don't have information on inventory or purchased quantities, but we observe the actual trade deal discount (Δw), then we would use a similar pass-through measure as in (A.3). The average pass-through over the two periods would be:

$$\beta_t = \frac{1}{2}\left(\frac{\Delta p_t}{\Delta w_t} + \frac{\Delta p_{t+1}}{\Delta w_{t+1}}\right) \tag{A.8}$$

Since $n_t^s < n_t^p$ and $\Delta w_{t+1} \leq \Delta w_t$ (i.e., a trade promotion tends to be followed by a higher wholesale price), this measure would systematically overestimate the pass through.

If instead, we use Average Acquisition Cost (AAC) to estimate pass-through, then since $I_{t-1}^f = 0$, $I_t^f = n_t^p - n_t^s$, and $n_{t+1}^p = 0$, we can show that $\Delta AAC_t = AAC_{\text{Reg}} - AAC_t = AAC_{\text{Reg}} - w_t$ and $\Delta AAC_{t+1} = AAC_{\text{Reg}} - AAC_{t+1} = AAC_{\text{Reg}} - w_t$. Thus

$$\beta_t = \frac{1}{2}\left(\frac{\Delta p_t + \Delta p_{t+1}}{AAC_{\text{Reg}} - w_t}\right) \tag{A.9}$$

While (A.9) using average acquisition cost is not identical to the true pass-through of (A.7), it is a better approximation to (A.7) than (A.8) which is based on observing the actual wholesale prices, but not accounting for forward buying. The intuition is that the carryover of the lower wholesale price de-biases the pass-through estimates in the presence of forward buying. Note that when sales in periods t and $t + 1$ are identical, (A.9) becomes equal to (A.7).

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