Undergraduate Economic Review

Volume 9 | Issue 1 Article 6

2012

Pricing Lower or Buying Cheaper? How Grocery Consumers Pay Less during Seasonal Demand Peaks

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Abstract

The average price paid for a seasonal grocery category is (surprisingly) lower during the category's seasonal demand peak. For several product categories at one supermarket chain, demand peaks are shown to be associated with 1) consumer substitution to lower-quality products, 2) product price reductions, especially on products that increase their market shares, and as a result 3) a decline in the average price paid for the product category. In one very seasonal category, price reductions are driven by intertemporal substitution associated with large weekly discounts. Findings are consistent with any of several loss leader models.

Keywords

loss leaders, seasonal demand, pricing, price index, price index decomposition, composition effect, intertemporal substitution, time-substitution, scanner data, supermarket, product quality

1 Introduction

Counter to basic economic theory for a competitive market, the retail price paid by consumers of a product category may be lowest during periods of peak demand (Chevalier, Kashyap, & Rossi 2003, hereinafter CKR). The market for canned tuna during Lent provides an example. During the forty days of Lent from February to April, some Christians abstain from meat consumption and consume more fish instead. This leads to a seasonal peak in demand for canned tuna (CKR). Yet alongside this exogenous increase in demand, there occurs a decline in the average retail price paid for canned tuna. Other product categories such as cheese, snack crackers, and beer experience similar price declines during holiday periods when consumers are likely to demand them most.

Past research is divided on how such price declines occur [1]. CKR suggest a loss leader explanation, in which stores discount and advertise a few highly demanded products in order to attract customers who then pay an undiscounted price for other goods. Nevo & Hatzitaskos (2006) (hereinafter NH) disagree, offering a demand-side explanation for the price decline. In their explanation, consumers often demand lower-quality products during peak demand periods. For instance, consumers who ordinarily drink high-quality beer might still bring low-quality beer to a Labor Day pitch-in. This shift to cheaper products would depress the average price paid for the product category, even if the prices of individual products were not changing.

CKR and NH thus disagree not only on why peak demand price declines occur, but on how. Are retailers pricing lower during peak demand periods, or are consumers buying cheaper products? An answer to this question will be needed to evaluate any loss leader model or other theory of seasonal pricing.

CKR and NH reach these opposing conclusions despite analyzing the same set of scanner data: eight years of sales at a Chicago supermarket chain. This paper reexamines the same data, decomposing each peak demand price decline into reductions in the retail prices of individual products, consumer substitution among products, and consumer time-substitution. Through this decomposition, some consistent patterns emerge. First, consumers substitute to lower-quality products during peak demand periods (as suggested by NH). Second, retail price reductions on individual products contribute substantially to the category average price declines (as suggested by CKR). Price reductions on lower-quality products tend to be especially large. In summary, inexpensive products are both more heavily discounted and more heavily purchased during peak demand periods.

[1] One possible explanation is a decline in the retailer's costs. However, CKR examine wholesale price data to show that cost changes cannot adequately explain the retail price declines.

Finally, consumers may substantially reduce their expenditure by timing their purchases to coincide with discounts. In the canned tuna category, the correlation of purchases and discounts reduces peak demand period prices by as much as 40 percent for some products. Care must be taken to distinguish the time–weighted average price offered by the retailer from the (sometimes much lower) sales–weighted average price paid by consumers.

Overall, findings are consistent with any of several loss leader models, including the model formulated by Lal & Matutes (1994) and suggested for these data by CKR. In the Lal-Matutes model, retailers attract customers by discounting and advertising those products that are most heavily purchased. This allows retailers to save on advertising expenses, since they can advertise just a few products while still promising large savings to their customers.

NH challenge the relevance of the Lal-Matutes model, claiming that discounts are mainly focused on products with low and declining market shares. If this were the case, the Lal-Matutes model would not justify the observed choice of products to discount. However, this paper incorporates consumer time–substitution to show that products with increasing market share were indeed experiencing large discounts, consistent with the Lal-Matutes model.

This paper identifies peak demand price declines and decomposes them into distinct constituent factors. Section 2 identifies six significant seasonal declines in the average price paid for a product category. Section 3 decomposes each price decline into a reduction in product prices, a shift to lower-quality products, and an interaction of these two effects. Section 4 examines one major cause of falling product prices: consumer substitution across time periods and/or stores. Section 5 illustrates with a product-level examination of the canned tuna category. Section 6 concludes with implications for loss leader and other models.

2 Data

This paper examines the Dominick's Finer Foods (DFF) database, provided by the James M. Kilts Center, University of Chicago Booth School of Business. This scanner dataset, also used by CKR and NH, details sales of a Chicago supermarket chain from 1989 to 1997 [2]. For this analysis, only seasonal product categories are of interest. These include beer, cheese, snack crackers, and canned tuna [3].

[2]Due to sparse data for the final year, this analysis uses only data from September 1989 through January 1996

[3]Although soft drinks may also experience seasonal demand, they suffer from some coding problems in this dataset. I follow CKR in excluding them. In addition, I follow NH in excluding CKR's

Seasonal peaks in sales volume include Lent (for canned tuna) and Thanksgiving and Christmas (for cheese and snack crackers). Beer has several seasonal peaks in volume, coinciding with various summer holidays (Memorial Day, the Fourth of July, Labor Day).

As noted by CKR, each of these occasions is associated with a cultural tradition of consumption. For instance, Lent is traditionally marked by abstaining from meat and consuming more fish. Labor Day is a traditional occasion for picnics and beer consumption. Thus there is reason to suspect that an increase in sales volume for any of these occasions would reflect an increase in the level of demand.

Table 1 shows changes in sales volume for each of the above occasions. Weekly sales volume (in ounces or fluid ounces) is regressed on a peak demand period dummy (set to 1 during the peak demand period and 0 outside it) and on a linear and a quadratic time trend (i.e. week and week squared). Only the coefficient on the peak demand dummy, β_{peak}, is shown. Following CKR, sales volume is divided by the number of DFF stores doing business in a week, correcting for store openings and closings. Each of the demand peaks studied is associated with an increase in sales volume of at least 25 percent. Column 4 of Table 1 repeats the regression, but with average price per ounce (or fluid ounce) as the dependent variable. Price is measured here as average revenue in a week divided by total ounces (or fluid ounces) sold that week. Standard errors are shown in parentheses.

Counterintuitively, six of the eight demand peaks are associated with a significant decline in the average price paid by consumers. Only one demand peak (cheese at Thanksgiving) is associated with a price increase, and it is neither economically large nor statistically significant. Consumers pay the least per unit of product at the same time they are buying the most units.

3 Price and composition effects

Declines in average price paid during peak demand periods can be expressed as a combination of changes in product prices and changes in market shares. Consider the average price paid for a product category, as measured by the dynamically weighted price index:

$$P_t = \sum_j P_{jt} w_{jt}. \tag{1}$$

Here P_{jt} is the price per ounce of product j in period t, defined as the product's

two categories of cooking soups and eating soups. Finally, I exclude the oatmeal category, where a complete analysis may require the historical weather data used by CKR.

Product Category	Demand Peak	β_{peak} on volume	β_{peak} on price
Tuna	Lent	0.580** (0.126)	-0.124** (0.021)
Beer	Memorial Day	0.418** (0.125)	-0.033 (0.039)
	4th of July	0.618** (0.108)	-0.085* (0.035)
	Labor Day	0.356** (0.113)	-0.086* (0.035)
Cheese	Thanksgiving	0.275** (0.056)	0.035 (0.022)
	Christmas/New Year's	0.377** (0.041)	-0.073** (0.017)
Snack Crackers	Thanksgiving	0.382** (0.070)	-0.049* (0.019)
	Christmas/New Year's	0.618** (0.046)	-0.108** (0.014)

* Coefficient significantly different from zero at the 5 percent level.

** Coefficient significantly different from zero at the 1 percent level.

Table 1: Seasonal peaks in sales volume for four product categories. Column 3 shows the coefficient on a seasonal demand peak dummy when weekly sales volume is regressed on this dummy and on linear and quadratic time trends. Column 4 shows the coefficient on the demand peak dummy when the dependent variable is weekly price rather than sales volume. Dependent variables are normalized to mean 1 to facilitate comparisons between product categories.

period t revenue divided by its period t sales volume in ounces. w_{jt} is the market share by weight of product j in period t. The price index P_t is thus the average price per ounce paid for the product category in period t. For this paper, data are divided into just a few time periods. All occurrences of the same demand peak are aggregated into the same time period, so that the Christmas time period includes several weeks around Dec. 25 1989, several weeks around Dec. 25 1990, and so on through Dec. 25 1995 [4]. All weeks not within four weeks of the peak demand period are used to form a baseline period.

Changes in P_t may be caused by either of two factors, or by an interaction between them. First, the prices P_{jt} may change between periods—a ”price effect”.

[4]Price and sales volume for each category vary secularly as well as seasonally. However, peak demand price declines are robust to detrending, as seen in Table 1.

Second, some products may gain or lose market share w_{jt}—a "composition effect". For example, if a product with a low price increases its market share, the effect will be a decline in the overall price index. Finally, an interaction effect emerges when prices and market shares vary simultaneously.

We can isolate either the price or composition effect by holding either the w_{jt}'s or the P_{jt}'s fixed at base period values during the peak demand period. For instance, let 0 be the base period and 1 be the peak demand period. We can isolate the price effect (PE) in the peak demand price change as

$$PE = (\sum_j P_{j1} w_{j0}) - P_0. \tag{2}$$

The composition effect (CE) can be found similarly as

$$CE = (\sum_j P_{j0} w_{j1}) - P_0. \tag{3}$$

We are left with only the interaction effect, which is the residual price change after accounting for the price and composition effects. This can be computed as

$$P_1 - P_0 - (PE + CE) = P_1 + P_0 - (\sum_j P_{j1} w_{j0}) - (\sum_j P_{j0} w_{j1}) \tag{4}$$

Fig. 1 applies this decomposition to each peak demand price decline. It is difficult to say which effect is generally most important; the price effect dominates in two demand peaks and the composition effect in three. For canned tuna during Lent, all three effects play a major role [5]. Overall, product price reductions and shifts in purchasing patterns are both central to the price declines seen here.

Previous analyses of the DFF data (CKR, NH) have addressed price and composition effects by comparing the movements of a fixed-weights and a dynamic-weights price index. A fixed-weights index captures only price effects, while a dynamic-weights index captures the entire change in consumer expenditure per ounce. Such price index analysis is sufficient to draw several important conclusions. CKR observe a decrease in their fixed-weights price index during peak demand periods and conclude that DFF is reducing individual product prices at these times. NH point to the much larger decrease in a dynamic-weights price index to emphasize the importance of a changing product mix.

However, a comparison of price indices does not distinguish between composition effects and their interaction with price effects. Here, the interaction reflects the degree to which discounted products increase their market shares. A rising market

[5] The total price declines in Fig. 1 are generally larger than the coefficients in the price regression of Table 1. This is in part due to the tendency of consumers to buy more in weeks with lower average prices. This tendency is explored further in Section 4.

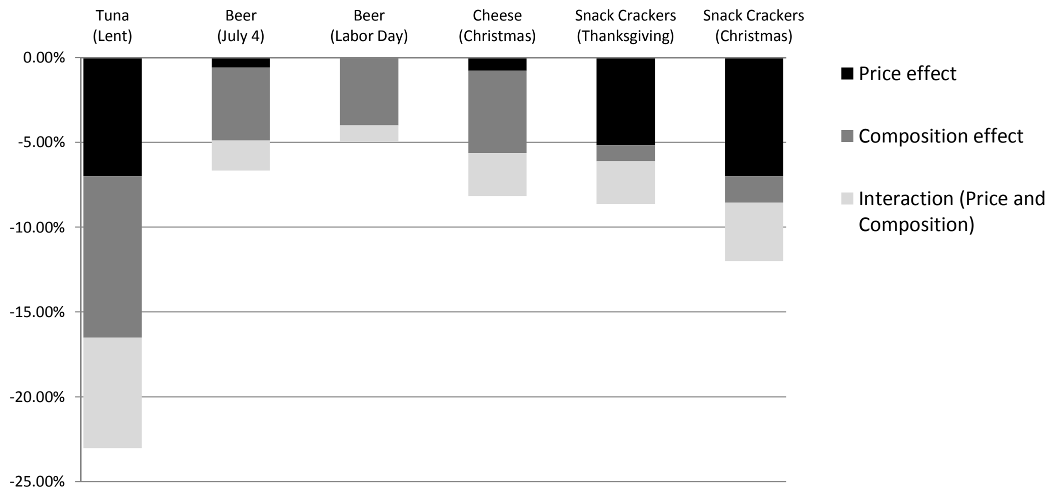

Figure 1: Decomposition of price declines into a price effect, a composition effect, and an interaction term. Of the eight demand peaks in Table 1, only the six that experience significant price declines are reported here. To prevent peak demand effects from spilling over into the rest of the year, non-peak data end four weeks before the peak begins and begin four weeks after it ends. Products with very sparse data are excluded from this analysis.

share amplifies the effect of a falling price on the category price index, as seen in Equation 1. Interaction terms play a substantial role during peak demand periods, accounting for about a quarter of most price declines in Fig. 1. The implication is that during peak demand periods, price reductions on a product are associated with an increase in the product's sales volume. This result is confirmed by a regressing a measure of volume change on a measure of price change (Table 2).

4 Consumer use of discounts

Supermarkets generally set prices on a weekly basis, singling out some products for special discounts and promotions. DFF's prices can also differ across stores (although advertised discounts are generally uniform across the chain). The average price paid for a product is thus bilaterally determined, by a retailer setting many different prices across store–week pairs and by consumers arranging their purchases in response. Just as the choice to buy StarKist rather than Chicken of the Sea affects the average price paid for tuna, the choice of when and where to buy StarKist affects the average price paid for StarKist.

To formalize the above argument, let p_{jt} be the simple average of per-ounce

Product Category	Demand peak	$\beta_{\text{price\_ratio}}$
Tuna	Lent	-0.819** (0.082)
Beer	Memorial Day	-1.782** (0.402)
	4th of July	-0.373** (0.049)
	Labor Day	-0.573** (0.181)
Cheese	Thanksgiving	-0.206* (0.086)
	Christmas	0.229 (0.491)
Snack crackers	Thanksgiving	0.090 (0.088)
	Christmas	-0.119 (0.398)

* Coefficient significantly different from zero at the 5 percent level.

** Coefficient significantly different from zero at the 1 percent level.

Table 2: Regression of the ratio (peak volume)/(non-peak volume) on the ratio (peak price)/(non-peak price) for each product in each seasonal category. In five of eight demand peaks, falling prices are associated with rising market shares (at a 5 percent significance level). The other three categories showed insignificant results.

prices for product j across all store–week pairs in multi-week period t. This is the expected price a consumer would pay for product j if he purchased in a random store and week, without regard for discounts. Let P_{jt} be the actual average price per ounce paid for product j in period t. As in Section 3, each P_{jt} is computed as product j's period t revenue divided by its period t sales volume in ounces. Define a "discount utilization factor" f_{jt} by

$$P_{jt} = p_{jt} f_{jt}. \tag{5}$$

Thus f_{jt} is the fraction of p_{jt} that consumers actually pay. An f_{jt} much less than 1 indicates that consumers are successfully reducing their expenditure on product j by buying at the lowest prices offered. This discount-correlated (and perhaps discount-driven) substitution increases the price impact of retailer discounts.

Discount-correlated substitution can also affect the average price paid for a category of products. We can quantify this effect by isolating the effect of the f_{jt} on

the category average price. For each product category, the average price per ounce paid by consumers in period t is

$$P_t = \sum_j p_{jt} f_{jt} w_{jt}. \tag{6}$$

As in Section 3, we can isolate the effect of one or more determinants of price by holding all other determinants fixed at base period values during the peak demand period. Fig. 2 incorporates the f_{jt} into the decomposition of peak demand price declines. Using observed values for market shares, simple average prices, and actual average prices paid, we can decompose the decline in P_t during each demand peak. Note that in some cases, one or more determinants of category average price may work against the price decline. For instance, the interaction of price and composition effects for snack crackers during Christmas lessens the price decline during that period. This indicates that unlike in other demand peaks, reductions in average prices offered fell most heavily on products with declining market shares. Similarly, reductions in the impact of the f_{jt} lessen the price declines for beer in both the Fourth of July and Labor Day peaks. However, these effects had a negligible impact on beer's average price paid (< 0.2 percent).

In most of the demand peaks, discount-correlated substitution has only a small effect on the category price change. Canned tuna during Lent and snack crackers near Christmas are the exceptions. In the case of canned tuna, changes in the f_{jt} account for almost half the total price decline. This indicates that the Lent price decline is not just due to an overall reduction in prices offered, or to consumer substitution to discounted products. Rather, consumers during Lent are arranging their purchases of certain tuna products in a way that takes advantage of those products' lowest prices.

NH do not consider discount utilization in their treatment of product prices, instead taking a simple average of price over all store-week pairs. This approach can produce misleading results for individual product prices and for category price indices, especially in the canned tuna category that forms NH's main focus. Referring to Fig. 2, almost half of canned tuna's price decline during Lent is attributable to discount utilization reducing prices on individual products. Omitting this effect, NH are left with a large price reduction from changing market shares (9.53 percent in this analysis), a small price reduction from changes in simple average prices (2.73 percent), and a trivial interaction between the two (0.12 percent). NH are thus led to attribute falling tuna prices to shifting brand choices. In reality, discounts and discount-correlated substitution play an equally large role, contributing another 10.65 percentage points to the price decline. Contrary to NH, the Lent price decline is not mainly driven by a composition effect across brands.

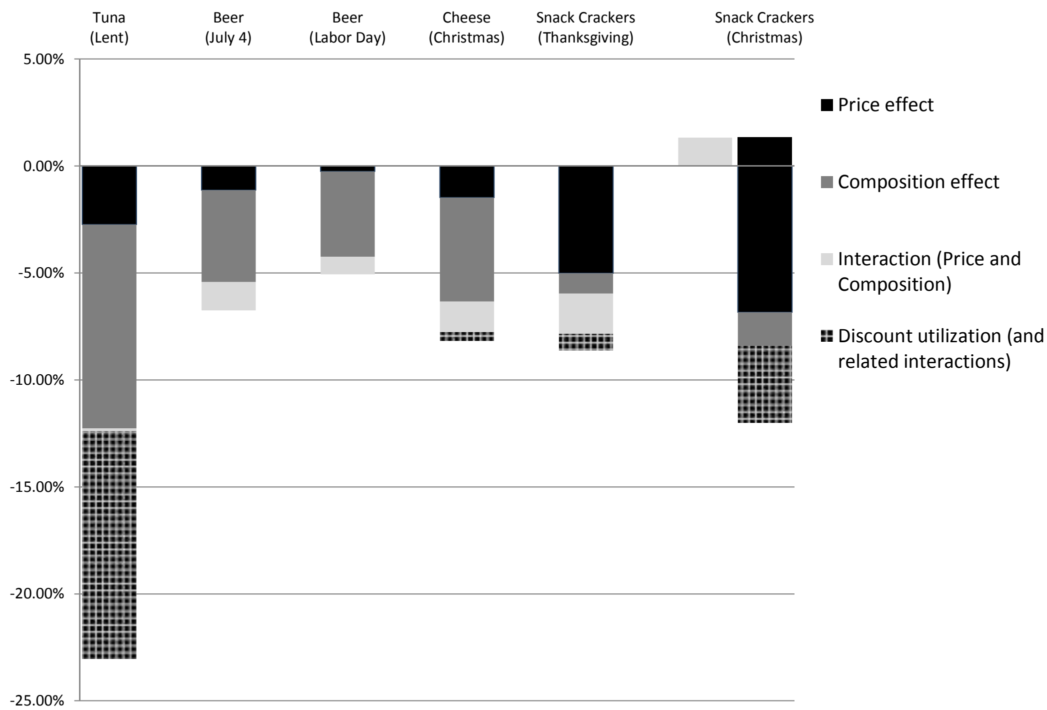

Figure 2: Decomposition of peak demand price declines into changes in product prices, changes in market shares, an interaction term, and changes in the impact of temporary discounts. Of the eight demand peaks in Table 1, only the six that experience significant price declines are reported here.

5 Illustration: Canned Tuna

A closer look at the canned tuna category demonstrates how peak demand price declines may occur. As recognized by NH, canned tuna exemplifies the seeming paradox of falling prices in seasonal demand peaks. A four-week Lent shopping period is associated with a substantial volume increase (over 50 percent) and a sharp drop in price (23 percent). Fig. 1 shows another interesting characteristic of canned tuna: a price effect, a composition effect, and an interaction between them are all important factors in tuna's price decline. Much of the price reduction is related to an increase in consumer utilization of weekly discounts (Fig. 2).

Tuna's price decline can be fully decomposed using the notation of Equations 1–6, as in Figs. 1 and 2 . Table 3 shows the empirical values of P_{jt}, p_{jt}, and w_{jt} for major products in Lent and non-Lent periods. Values of f_{jt} are computed as P_{jt}/p_{jt}. Data are divided into two periods: a Lent shopping period L and a non-Lent period N.

#	Brand	Size (oz.)	$P_N(¢)$	$P_L(¢)$	$p_N(¢)$	$p_L(¢)$	$w_N(\%)$	$w_L(\%)$	$f_N(\%)$	$f_L(\%)$
1	COS	6	12.2	7.4	13.3	13.1	8.7	25.1	91.9	56.1
2	SK	6.12	12.3	10.6	13.2	12.1	14.7	15.8	93.0	87.2
3	BB	6.12	10.6	10	12.9	12	10.1	11.4	82.5	83.2
4	COS	6	12.4	7.1	13.3	13.1	2.6	7.3	92.9	54.4
5	DOM	6.5	11	10.5	11.6	11.2	5.4	4.2	94.3	94.0
6	SK	6.12	12.4	10.7	13.1	12.1	4.5	4.2	94.0	88.4
7	BB	6.12	11	10.1	12.8	12	3.0	3.6	85.6	83.7
8	COS	12.5	13.4	13.7	13.8	14	4.1	2.1	97.0	97.7
9	SK	12.5	14.4	14.5	14.8	14.7	3.6	1.9	97.2	98.8
10	GSA	6	24	23.7	24.2	23.8	2.9	1.9	99.1	99.7
11	GSA	13	22.3	21.8	22.5	22	2.5	1.6	99.4	99.1
12	BB	6.12	27.9	27.2	28	27.7	2.0	1.4	99.6	98.2
13	SK	6.12	28.1	27.3	28.3	27.6	2.0	1.4	99.1	99.0
14	SK	9	14.9	14.4	15.4	15.1	2.0	1.3	96.6	95.3
15	BB	12.2	27.7	27.2	27.6	27.3	2.1	1.3	100.3	99.7
16	COS	9.25	13.5	12.8	13.9	13.7	2.0	1.2	97.1	93.8
17	DOM	12.5	12.2	12.4	12.5	12.8	2.9	1.2	97.2	97.0
18	DOM	6.5	10.7	9.8	11.7	10.8	3.6	1.2	91.1	90.5
19	BB	6.12	22.1	19.9	22.5	21.1	1.6	1.1	98.1	94.3
20	3D	6	24.5	24.6	24.8	24.9	2.1	1.0	98.7	98.7
21	COS	6	25.8	26.6	27.3	27.2	1.5	0.9	94.4	97.5
22	COS	12.5	13.4	13.8	13.8	14.1	1.6	0.8	97.1	98.2
23	SK	9	22	21.2	22.2	21.6	1.1	0.8	98.9	98.2
24	BB	12.5	12.8	12.8	13.2	12.8	1.4	0.6	97.0	99.4
25	COS	6.5	15.4	15.2	15.5	15.4	1.2	0.5	99.0	98.7
26	SK	3.5	30.4	30.5	30.4	30.3	0.8	0.5	100.1	100.7
27	SK	6.12	25.8	25.7	25.8	25.6	0.9	0.5	99.9	100.1
28	SK	9.75	26.3	26.4	26.1	26	0.8	0.5	101.1	101.3
29	SK	6.12	16	16.8	16.3	16.8	1.0	0.4	98.3	99.8
30	BB	6.12	27.9	27.3	28	27.7	0.6	0.4	99.7	98.5

(Brands: COS = Chicken of the Sea, SK= Starkist, BB = Bumble Bee,
DOM = Dominick's private label, GSA = Geisha, 3D = 3 Diamonds)

Table 3: Canned tuna products sold by DFF in 1989-1995, excluding those with sparse data. Columns show average price paid by consumers (P), a simple average of prices offered (p), market share (w), and fraction of simple average price paid by consumers (f). Values are given for both Lent (L) and non-Lent (N) periods. A four-week buffer is placed on either side of the Lent period, to prevent peak demand effects from spilling over into the non-Lent data. Only the top 30 products (by weight sold during Lent) are shown here, but 52 products are used in the analysis. The remaining products have a total market share of less than 4 percent.

The most striking observations from Table 3 concern products #1 and #4, Chicken of the Sea (COS) Chunk Light Tuna in Water/Oil, 6 oz. These two products were purchased much more cheaply during Lent than in the rest of the year, with decreases of about 40 percent in the price paid by consumers. However, neither product substantially reduced its simple average offered price p. The reduction in price came instead from an increase in the importance of weekly discounts, as measured by f. Perhaps in response to their large price reductions, products #1 and #4 nearly triple their market shares during Lent. Taken together, the two products account for most of the tuna category's 23 percent decline in price paid.

The two COS products are of below average quality, in that they are priced lower than other brands throughout the year. On average, canned tuna sells for 16 cents per ounce outside Lent, while both COS products sell for an average of 13.3 cents per ounce in the same period. Their price reductions and market share increases during the Lent demand peak are a repetition of tendencies seen in other product categories in Section 3. Low-quality products tend to increase their market shares, and products with increasing market shares tend to reduce their prices.

The COS products also demonstrate the importance of discounts during peak demand periods. Figure 3 shows the distribution of prices over stores and weeks for one of the COS products (#1) during Lent and during the rest of the year. We see that DFF offers deep discounts more frequently during Lent. For instance, prices less than \$0.10 per ounce are very rare outside Lent, occurring in only 2 percent of week-store pairs. But in Lent, 9 percent of week-store pairs have prices below this threshold. Consumers seeking large discounts can find them more easily during Lent. This may lead to the decline in this product's f_{jt} seen in Table 3. An increase in discount-seeking behavior by consumers could also play a role [6].

Omitting consumer responses to weekly discounts may give misleading results about the prices of the COS products, and about the tuna category as a whole. Consider NH's product-level approach to identifying peak demand price declines. For each product, prices were gathered across all store-week pairs. Prices were then regressed on a peak demand period dummy and several controls. While this approach would identify a decline in the simple average price p_{jt}, it would miss the impact of consumer utilization of weekly discounts. Changes in P_{jt}, even up to the 40 percent observed here, can go unobserved. When consumers shift their purchases to take advantage of weekly discounts, a simple average of offered prices may not accurately summarize prices paid.

[6] Warner & Barsky (1995) posit that consumers invest more effort in search behavior when their level of demand is highest. This is because savings scale linearly with the quantity to be purchased, while search costs remain fixed.

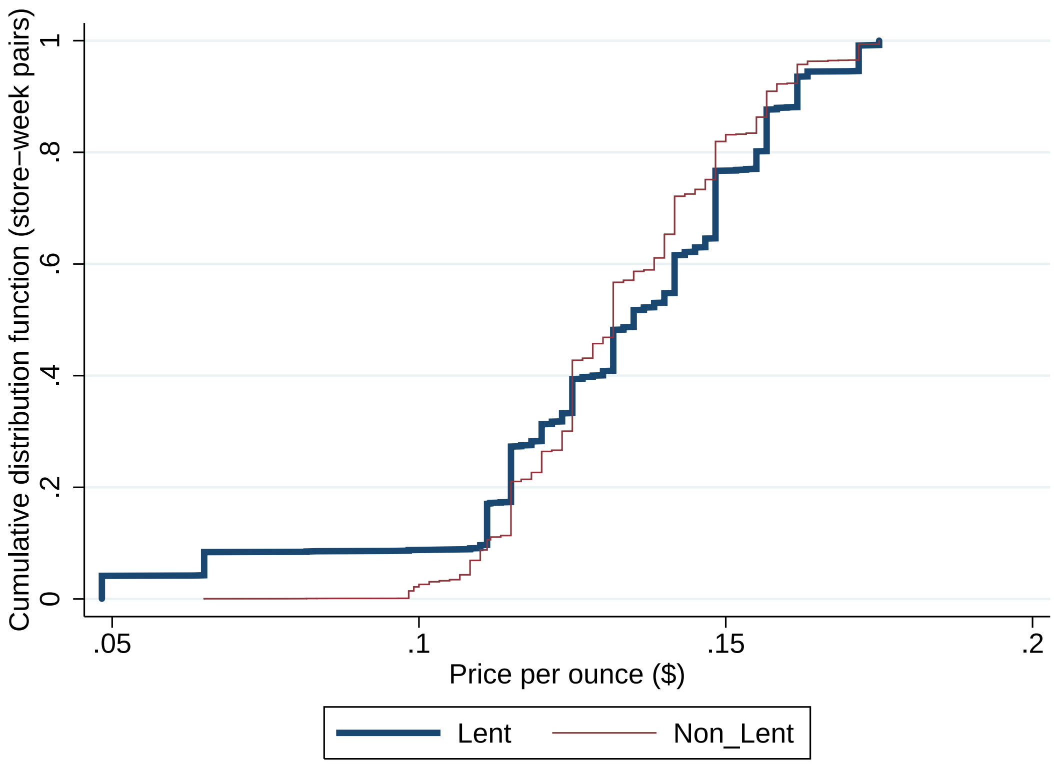

Figure 3: Distribution of price per ounce for Chicken of the Sea Chunk Light Tuna in Water, 6 oz. Distributions are taken across all store-week pairs. Separate distributions are given for Lent and the rest of the year. Note the increased prevalence of very low prices during Lent.

Since NH do not observe the price declines on the COS products, they conclude that increases in their market share are due to changes in brand preferences or price sensitivity. The large price declines seen here show that no such preference shifts were necessary. Essentially, the change in COS market share could be explained as a movement along a demand curve rather than a change in the shape of the curve. Although we cannot rule out a shift in preferences, we need not assume that preference shifts were the main cause of the decline in canned tuna's average price.

6 Conclusion

Overall, the patterns found in peak demand price declines are consistent with the loss leader model of Lal & Matutes (1994) and CKR. The retailer reduced prices on low-quality products in categories where it anticipated higher demand. This

amplified consumer substitution toward these products, adding a price motive to a purchasing shift perhaps initially driven by brand preferences. Peak demand price declines were thus a combination of declines in product prices and shifts to lower-quality products. In most product categories, both these factors played an important role.

In the tuna category, price reductions were accomplished by a few sharp weekly discounts and the associated substitution of purchases by consumers. This discount-correlated substitution had a powerful impact, accounting for nearly half of the overall Lent price decline (Fig. 2). This finding underscores the bilateral nature of price in situations where a product is sold across multiple locations or time periods. An overall "price" should summarize not the many prices that the seller offered, but the prices at which purchases actually occurred. When prices are volatile and consumers are price-sensitive, a simple average of offered prices may be far higher than the average price paid by consumers.

The strategy suggested by Lal & Matutes and CKR is by no means the only loss leader strategy a retailer could pursue. Simester (1996), Nagle & Novak (1988), and DeGraba (2006) offer loss leader models in which retailers use pricing policy to attract a certain type of customer to their stores. In the Simester and Nagle & Novak models, consumers are divided into types loyal to particular retailers and a type willing to shop around to maximize consumer surplus. A profit-maximizing retailer will seek to attract the surplus-maximizing shoppers by offering discounts on products mainly purchased by this type.

DeGraba's model differentiates consumers by profitability instead of loyalty. For instance, customers buying in bulk are likely more profitable than customers purchasing only a small quantity. Retailers attract more profitable customers by offering discounts on products usually purchased as part of a larger market basket. In DeGraba's example, turkeys may be heavily discounted near Thanksgiving, when they are bought by consumers preparing family dinners.

Since the DFF data are aggregated across customers, it would be difficult to establish which loss leader strategy best explains the results. Findings here are consistent with any one of them [7]. It is also possible that DFF combined several of these strategies or used some other strategy entirely. Further research with customer-level

[7] If DFF was following the Simester/Nagle & Novak strategy, then peak demand discounts on low-quality products would indicate that surplus-maximizing shoppers were especially likely to demand low-quality products during peak demand periods (or at least that DFF believed so). If instead DFF was following the DeGraba strategy, then peak demand discounts on low quality products would indicate that bulk shoppers were especially likely to demand low-quality products during peak demand periods (or that DFF believed so). Without customer-level data, it is difficult to evaluate these implications.

data might distinguish one loss-leader strategy from another in practice.

The DFF data show a multi-product retailer responding to cyclical demand with a cyclical pricing policy. However, neither multiple products nor cyclical demand is necessary for cyclical prices to be profit-maximizing. Varian (1980) showed that in a competitive single-product market, retailers might use cyclical discounts to charge a higher price to uninformed consumers. More recently, Su (2010) showed that consumer stockpiling can in some cases lead a single-product monopolist to engage in cyclical pricing. Such considerations present in single-product models may affect DFF's multi-product pricing choices as well.

Finally, accepting a loss leader model does not explain why lower-quality products might be heavily demanded during peak demand periods. One possible explanation is that products are being used differently at those times. In NH's example, consumers may demand a lower quality of canned tuna for tuna casserole than for tuna salad. Another explanation suggested by NH is a seasonal increase in consumer price sensitivity. While a loss leader model can explain retailer responses to changing preferences, it does not address the underlying reasons for preference changes. Again, customer-level data could be useful in resolving this question.

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