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ABSTRACT

For many products the average price paid by consumers falls during periods of high demand. We use information from a large supermarket chain to decompose the decrease in the average price into a substitution effect, due to an increase in the share of cheaper products, and a price reduction effect. We find that for almost all the products we study the substitution effect explains a large part of the decrease. We estimate demand for these products and show the price declines are consistent with a change in demand elasticity and the relative demand for different brands. Our findings are less consistent with "loss-leader" models of retail competition.

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1. Introduction

A number of previous papers documented that retail prices for many products tend to fall during periods of peak demand. Warner and Barsky (1995) show that the prices of several consumer appliances fall in the period prior to Christmas. MacDonald (2000) documents that prices of many food items decline in periods of seasonal demand peaks. Chevalier, Kashyap and Rossi (2003) (CKR, hereafter) use a unique data set provided by a large retailer in the Chicago area, and find that a price index for several products falls during periods of high demand. Examining these patterns carefully they conclude that the decline in average prices is best explained by loss leader models of advertising (Lal and Matutes, 1994).

It is somewhat counter-intuitive that prices do not rise during periods of high demand. As documented by previous work, cited above, this seems to be the case in a wide range of industries. Understanding what drives this is important for price theory and measurement. From the macro-economic point of view, sales are a major source of nominal price variation in many retail markets. Therefore, understanding what drives sales, and price rigidity during non-sale periods, has implications for the macro-economy (Warner and Barsky, 1995, CKR, Bils and Klenow, 2004.)

In this paper, we build upon CKR, using their data to provide support for an alternative explanation to the decline in the average price. Our explanation is based on a change in brand-level demand. We focus on two changes. First, price sensitivity can be higher during periods of high demand. If true this will lead to a lower equilibrium price. Demand might be more price elastic for several reasons. The mix of consumers might be changing. For example, increased demand for tuna during Lent comes mostly from a certain segment of the population that might have different price sensitivity. Furthermore, a given consumer might be more price sensitive because the product is used differently during a period of high demand. We provide examples below.

Second, the <u>brand</u> preferences within a product category might change. For example, eggs used in an Easter egg hunt can be of lower quality than eggs eaten at breakfast. Beer bought for a July 4th barbecue party can be of lower quality, either because of a public goods problem (you are unlikely to consume most of what you bring to the party), or because after a few beers it is hard to distinguish different brands. Most of the analysis in CKR is performed using a variable weights price index:[2] the prices of individual items are averaged using weights proportional to quantity sold. However, if preferences for brands shift towards cheaper products, then such an index could potentially be misleading. Even with no changes in prices a variable weights price index might change due to a composition effect.

In order to provide support for our explanation we re-examine the CKR data. We start by repeating their analysis using a fixed-weights price index. A fixed weights price index will not be affected by a change in the composition of brands, and therefore if that is all that is happening, it will show no decline. Indeed the results suggest that, for the product categories CKR identify as loss leaders, a fixed-weights price index displays much smaller price declines (in some cases none at all). Next, based on the initial analysis and for reasons we motivate below, we focus our attention on tuna, which faces a high demand peak during Lent. We find that much of the increase in the quantity sold is due to two products. These products, which are relatively cheap, nearly triple their market share and interestingly do not reduce their prices. Some of the competitors indeed lower their prices, in what seems to be a response to the decline in their market shares.

We also estimate weekly item-level demand for tuna. We find, as predicted by our explanation, that consumers are more price sensitive during Lent and that the brand preferences seem to change during Lent. Furthermore, we find no evidence that advertising is more effective during Lent, which is a testable implication of the loss-leader theory. While we focus on tuna, our results seem to be more general. We repeat the analysis for the other products studied by CKR and find similar results: we find evidence consistent with a change in price sensitivity and brand preferences, but less consistent with a theory of loss leaders.

There are two general lessons that can be learned from our analysis. First is the importance of seriously considering product differentiation and its implications for the results. CKR advocate the importance of incorporating retail behavior, but do so at the cost of treating the product as (essentially) homogenous. We, on the other hand, place more emphasis on product differentiation

[2]The paper also mentions brand-level analysis that was performed on a small number of brands.

and find different results. Second, our results show that one has to be careful in using prices paid by consumers to make inferences about supply side behavior. The observed prices might be driven, at least in part, by consumer behavior and not by pricing.

The explanation we provide here is similar to, yet distinct from, the one offered by Warner and Barsky (1995). They suggest that scale economies in search make the demand for the product more elastic during aggregate peak demand periods. We propose an explanation that is based on a change in the demand for the product during idiosyncratic peak demand periods. Moreover, our explanation is based on a change in the relative demand for different brands. These differences imply an alternative interpretation of the data. Indeed, some of our results, which we claim as support for our explanation, are similar to the results CKR use as evidence against the Warner and Barsky theory.

The rest of the paper is organized as follows. In Section 2 we summarize the basic patterns found by previous work and the models proposed to explain these patterns. In Section 3 we discuss our explanation in some detail. In Section 4 we present the data used in the analysis and a first cut at various price indices for different product categories. In Section 5 we focus on a single category, tuna. We estimate a brand level demand system and use it to show that: (i) price sensitivity increases during Lent; (ii) there seems to be a change in brand preferences for tuna brands during Lent; and (iii) there does not seem to be an increase in the efficiency of advertising during Lent. The first two findings support our explanation, while the third seems to cast doubt on the loss-leader story. We also show, in Section 5.3, that the results found for tuna are also mostly present in other product categories.

2. Previous Findings and Explanations

Temporary price reductions are common in many industries. Yet, it is only fairly recently that the economics literature has tried to empirically document and study patterns in these sales. Pashigian (1988) and Pashigian and Bowen (1991) study "clearance sales" in the fashion industry. In this industry prices tend to fall over the life cycle of the product. They find that markdowns increased over time, as variety increased, and are more common in some types of clothes, where variety and fashion are more important. They relate these findings to the predictions of a model of store uncertainty about the future popularity of colors, patterns and fabrics.

Warner and Barsky (1995) continue where Pashigian (1988) and Pashigian and Bowen (1991) left off. They collect four months of daily prices for eight items in several stores. The items they study include an action figure toy, bathroom towels, a bicycle and several small appliances. They find that prices tend to be marked down during weekends and before Christmas. Both are periods of (exogenously) high demand. They interpret these patterns as support for a theory based on increasing returns in the shopping technology. During periods of high demand consumers have a higher incentive to be informed about prices, thus, the demand faced by a retailer is more elastic, and therefore optimal prices are lower.

MacDonald (2000) documents a decrease in the price of food products at seasonal demand peaks. He uses the observed quantity data in order to select periods of high demand, i.e., a peak demand period is one in which the quantity sold is unusually high. He documents a decrease in the national average monthly price of narrowly defined items during periods of high demand. The analysis uses the largest selling item of the largest selling brand in each category. There are two potential problems with this analysis. First, the demand peaks are defined using the quantity data. In principle, the low prices might be causing the seemingly high demand. For some of the products he examines this might seem unlikely, yet for a large number of the products this might be the case. Second, a large number of products he examines have a peak in December, leaving the reader to wonder if this is just a seasonal effect that is not category specific.

CKR re-examine the issue, but through the quality of the data and the careful design of the study can address some of the potential problems in the MacDonald study. They use weekly item-level scanner data from a single retailer in Chicago. In addition to prices and quantities, they have a measure of wholesale price. We describe these data further below. Using this data set they examine prices during peak and off peak demand periods. One of the major differences in the analysis is that they define peak demand on *a priori* grounds, not using the observed quantity data. This allows them to deal with the potential endogeneity of the definition of peak demand. Furthermore, they focus on a smaller number of categories, carefully selected so that the peak demand periods do not fully overlap.

The first step in their empirical analysis is to document the decline in prices during the peak demand periods. Instead of focusing on a single item in each category they generate a varying-weights price index of the top items in each category.[3] The weights are proportional to the quantities sold of each item. They find that the log of the price index declines during peak demand periods.

Next they examine different theories that potentially explain the price declines. The first class of theories they consider are those that suggest that demand might be more elastic than usual during peak demand periods. Bils (1989) and Warner and Barsky (1995) are examples of such theories. The Warner and Barsky model suggests that, with fixed costs of search and travel between stores, consumers will search more during high demand periods. Thus, the demand facing a retailer will be more price elastic and the optimal price is lower.

A second class of models are those that focus on dynamic interactions between firms. In the spirit of Rotemberg and Saloner (1986), tacit collusion is sustained when the gains from defection (i.e., charging a price below the collusive level) in the current period are lower than the expected losses in future periods due to punishment. The incentive to cheat is highest during periods of peak demand since the current gains from cheating are higher. Therefore, the price level that can be sustained during high demand periods is lower. In examining the implications of this model CKR focus on retailer competition, mainly because their results seem to suggest that retail prices decline more than wholesale prices. Furthermore, they focus on competition across retailers for a basket of products and not on a product-by-product level.

The third and final class of models are loss leader advertising models. CKR focus on the formalization of Lal and Matutes (1994). In this model consumers do not know the prices of the goods until they arrive at the store. They pay a transportation cost to get to the store and to go from one store to another. If this cost is high enough the retailers will charge consumers their reservation

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[3]The exact number of items varies slightly between categories but is usually around 8-10.

price (which is assumed identical for all consumers) once they arrive at the store, and their transportation cost is sunk. Consumers foresee this strategy and therefore do not shop. The retailer's solution is to commit to a particular price by advertising it. If advertising was costless they would advertise all products. Lal and Matutes assume that retailers pay an advertising cost per item advertised. For items not advertised consumers assume that they will be charged their reservation. In this model prices are not pinned down: any of the goods could be discounted enough to attract consumers. As CKR show (in a two good case) if prices have to be non-negative then the retailer will prefer to discount the good with the higher demand. The intuition is simple. The discount needed for the lower demand product (given that the higher demand product will not be advertised and priced at the reservation price) makes its price negative. CKR interpret high demand as high demand relative to the typical demand for the product.[4]

CKR's main strategy to separate these models is based on separating periods of overall high demand (such as Christmas and Thanksgiving) and periods of product specific peak demand (such as tuna during Lent). The first two models have a prediction for why prices are low during the aggregate high demand periods but not during idiosyncratic peak demand periods . CKR show that prices decline even during periods of product specific peak demand (e.g., tuna during Lent). They provide two additional pieces of information. First, by estimating category-level demand regressions they show that the overall demand does not seem to be more elastic, providing direct evidence against the Warner and Barsky theory. Second, they show that products that are in peak demand are more likely to be advertised.

There are a couple of reasons to be somewhat suspicious of the loss leader theory. First, which product goes on sale is determined by the non-negativity constraint: a retailer puts the product on sale that allows a large enough discount. While this effect is clear in a simple model, it seems somewhat unlikely that in a real world market, with many additional complexities, this constraint will bind. Second, and somewhat related, many of the products CKR examine are a small part of the

[4]Taken literally the model's definition of high demand is different: it is high demand relative to the other products. Thus, a product with seasonally high demand could still be a low demand product.

overall expenditure of a household in any given shopping trip. For example, a can of tuna costs roughly 80 cents. Even if a household buys five cans during a high demand period and the discount is 20 cents, or 25 percent (a much larger discount than what we see in the data), then the savings are one dollar. Surely there are other ways to offer such, or much larger, savings.

3. Our Explanation

In this section we offer an alternative explanation as to why the average price declines during peak demand periods. This explanation is consistent with prior findings, surveyed in the previous section. In addition, we discuss the empirical implications that allow us to separate our explanation from the loss leader model proposed by CKR. In the next sections we test these implications.

Our explanation relies on a change in brand-level demand. We focus on two changes in particular: a change in demand elasticity and in relative demand for different brands during peak demand for the category. The shift in the aggregate, or average, price sensitivity can occur for several reasons. The demand of certain households might increase more than others (consider, for example, the demand for tuna during Lent). If price sensitivity varies by households, then the aggregate price sensitivity will differ between Lent and non-Lent periods. Alternatively, even for a given household price sensitivity might vary if the use of the product changes. We provide some examples below.

While overall demand for a product (e.g., tuna) might increase, we claim that the increase might be different for different brands (e.g., StarKist). There are several reasons why this might occur. First, there might be a shift in household-level demand for different brands. Consider the case of canned tuna. It could be used for various dishes, including tuna salad or tuna casserole. These different uses might require different quality. For example, tuna casserole might require a lower quality brand. If during Lent tuna casserole is eaten more frequently than tuna salad, relative to non-Lent periods, then the relative demand for different brands will change.

Second, if we think of brands as representing different quality, then there might be decreasing marginal utility from quality. Consider the example of beer during July 4^{th}. A consumer who might normally prefer a high quality beer might prefer a lower quality (and cheaper) brand during July 4th. This might be either because after a few beers it is harder discern their quality, or because of a public goods problem: if you bring beer to a party, for the most part it will be consumed by others.

Third, just as is the case for price elasticity, even if brand preferences at the household level remain constant there could be a change in the relative weights of different households. Not all households increase their demand proportionally. Suppose there are two types of households. Type A prefer brand 1 and type B prefer brand 2. If households of type A have a larger increase in demand for the product than the overall relative increase in demand will be higher for brand 1.

There are several implications of our explanation that distinguish it from alternatives. First, our explanation implies that the effect on a category-level price index will be different if one uses a fixed-weights index versus a variable weight index. Since we claim there is a change in brand preferences during some periods of high demand, then the change in weights is systematic, and we expect the fixed weights index to give a different answer. In particular, if the shift is towards cheaper brands, then we expect the fixed weights index to exhibit smaller drops during high demand periods. Indeed, if all that is happening is a shift between brands, then this index should not drop at all.

Second, in order to test our explanation directly we look at brand-level data. We examine prices of different brands to see which brands reduce their prices during periods of high demand. We also examine quantities to see if all brands experience an increase in demand during periods of category high demand. Finally, we estimate a brand-level demand system, allowing price sensitivity and brand preferences to change between high demand periods and other periods.

Third, loss leader models imply that the effectiveness of advertising should be higher during high demand periods. During non-peak demand periods advertising serves to induce brand switching and also potentially bring consumers to the store. According to the loss-leader model, the aggregate effect of bringing consumers to the store is much larger, during peak demand periods, since overall demand is higher. Therefore, a brand's increase in demand due to advertising, should be much larger during peak demand periods. Our model does not imply a differential effect of advertising. So we can test this directly in a brand-level demand system.

4. Data and Preliminary Analysis

4.1 *Data*

The data set used for the analysis is the same as the one used by CKR, and comes from the Dominick's Finer Foods (DFF) database at the University of Chicago Graduate School of Business. DFF is the second largest supermarket chain in the Chicago metropolitan area, with a market share of approximately 25 percent. The data are weekly store level data by universal product code (UPC) and include units sales, retail price, profit margin (over the average acquisition price)[5] and a deal code. The deal code indicates what type of promotional activity, if any, took place. CKR report some mistakes in the classification of the various activities. Thus, we will only use a binary variable which equals one if any activity took place. The data cover approximately 400 weeks starting September 1989, in 29 different product categories. The data, including a detailed description of the variables and the collection process, can be found at http://gsbwww.uchicago.edu/kilts/research/db/dominicks.

The key variables are defined, following CKR, as follows. Holiday dummy variables, which capture high demand periods around holidays, equal 1 for the two weeks prior to the holiday, zero otherwise. The Lent dummy variable equals 1 for the four weeks preceding the two week Easter shopping period. The post Thanksgiving dummy variable equals 1 for the week following Thanksgiving. The Christmas dummy variable equals one for the two weeks prior to Christmas as well as the week after, in order to capture the New Years's shopping period.

We supplement the DFF data with weather information from the Chicago Mercantile Exchange daily data, creating weekly temperature corresponding to the DFF weeks. Using the mean temperature (TEMP) we generated two variables: HOT = max(0, temp-49), COLD = max(0, 49-temp). Forty nine degrees Fahrenheit is approximately the mean, and median, temperature in Chicago.

[5]Using the retail price and the profit margin we will recover the average acquisition price. Note that while we refer to it as the wholesale price, it is not the economic marginal cost faced by the retailer.

We focus on the categories that CKR identified and we follow their definitions of a-priori high demand periods. One of the advantages of following the CKR classification is that it is pre-determined from our point of view. The categories we study are tuna, beer, oatmeal, cheese and snack crackers. CKR study two additional seasonal categories: eating soup and cooking soup. We decided to not examine these categories, since we felt uncomfortable in our ability to classify products into each category. We also do not study the non-seasonal categories identified by CKR (analgesics, cookies, crackers and dish detergent), since they seem to have little relevance for our explanation. Summary statistics for the main variables for each of the product categories we used are displayed in Table 1.

The expected periods of peak demand for each category, identified by CKR, are as follows. For beer, hot weather, Memorial Day, July 4th, Labor Day and Christmas. The logic is that the summer holidays are peak picnic time and Christmas includes a run up to New Year's Eve. We also added Superbowl Sunday. For tuna, the expected peak demand is Lent, a period in which many Christians abstain from eating meat and eat fish instead. The cheese category has an expected peak during Thanksgiving and Christmas, when cheese would either be used for cooking or served at parties. A similar logic applies to peak demand for snack crackers at Thanksgiving and Christmas. Finally, consumption of oatmeal is expected to go up during cold weather.

For each category we include the top 30 UPC's. These products account for a significant share, as can be seen in the last row of Table 1.

4.2 *Preliminary Analysis*

Before we examine the behavior of prices we present in Table 2 the change in total quantity sold aggregated across stores and products within a week. The dependent variable is the quantity sold, measured in thousands of pounds. Similar results can be found if we use either revenue or quantity measured in units.

Next we examine the behavior of category level price indices. The indices are computed in the following way. The price data are collected by store, UPC and week. Let P_{jst} be the price per ounce of product (i.e., UPC) j at store s in week t. The price index in time t is

$$P_t = \sum_{j,s} w_{jst} \cdot P_{jst}$$

where w_{jst} are weights. We report results using two price indices. The first is a variable weight price index, in which w_{jst} is the quantity share of product j sold in store s in week t of the total quantity sold in t. The second is a fixed weight in which w_{jst} is the quantity share of product j sold in store s in the sample period of the total quantity sold in the sample period, normalized so the shares in each week sum to one. The variable weight index is analogous to the one used by CKR (we discuss the difference below). We also report results where we replace the retail price with the retail markup (retail price minus the wholesale price). We also computed, but do not report, these indices using revenue shares instead of quantity shares, and using the logarithm of price instead of price.

Table 3 reports results from OLS regressions where the dependent variable is the weekly price index in each category. In columns titled *Fixed* and *Variable*, the price index is a fixed- and variable-weight price index, respectively. As we described in the previous section we focus on the categories identified by CKR as having potential for loss leader periods. Bold type indicates a period of expected high demand peaks, following CKR's classification.

Examining the results in the *Variable* columns we generally find results similar to CKR. The price index tends to go down during expected high demand periods. Our results tend to be less significant than theirs, and we tend to find more unexpected price reductions (for example in the cheese and snack crackers categories). The differences between our results and CKR's finding could be explained by differences in the construction of the data. The set of UPC's we use do not match exactly: we have a larger number of UPC's. We created the index using price, instead of logarithm of price, and quantity shares, instead of revenue shares. Finally, we report ordinary least square results, with robust standard errors, instead of generalized least squares. Of all of these, the difference that seems to matter the most is the functional form. Repeating our analysis using the logarithm of price we re-produce almost exactly the CKR numbers.

The results in the *Fixed* columns tend to present a somewhat different picture. Several of the expected effects are no longer statistically significant. Furthermore, some of the effects are much smaller in magnitude. For example, the coefficient on Lent in the tuna category using the fixed-weights index is roughly a third of the same coefficient using a variable-weights index. This suggests that much of the reduction in the average price of tuna during Lent is coming from a substitution effect, as we suggested.

The prices of tuna during Christmas and Thanksgiving provide us with another opportunity to see how the two price indices differ. The results in the *variable* column suggest that the price of tuna during Christmas and Thanksgiving is higher. One could think of this as evidence for the loss-leader story: since the demand for tuna is low during these periods they are not used as loss-leaders and are therefore less likely to be on sale. However, when we look at the results in the *Fixed* column a different picture emerges. It is not that tuna is more expensive, but that there seems to be substitution towards more expensive brands, a result that is both intuitive and consistent with our explanation.

If all that was happening during peak demand periods was a substitution effect, then the fixed-weights index would not change. The fact that it is decreasing suggests that at least some products are reducing their price. That, in most cases, the reduction in the fixed weights index is substantially smaller than the reduction in the variable weight index, suggests that a large part of the story is due to a change in composition. The remaining drop is due to a reduction in prices that could be due to several stories that we try to separate below.

CKR motivate the use of a variable weights index by claiming that the products are close substitutes and therefore from the consumer's perspective this is the relevant measure. They claim that a fixed weights index will not capture the effective price level. Whether or not these brands are indeed close substitutes is an empirical matter. However, even taking their claim as given, this is not the relevant argument. We are not asking if consumers are better or worse off. We are using the price index to summarize an average price in order to learn about the supply side.

In Table 4 we present results from the same regressions as those reported above, using markups as the dependent variables. In order to construct the markup we subtracted the average acquisition cost from the retail price. If a price reduction was completely driven by a change in the retail price, then the coefficients in Table 4 should be identical to those in Table 3. On the other hand, if the price reductions are only because the wholesale price drops and the reductions are passed-through completely to consumers, then the coefficients in Table 4 should be insignificant.

The results for the tuna and oatmeal categories suggest that much of the price reductions in these categories during Lent and cold weeks, respectively, are driven to a large extent by changes in the wholesale prices. On the other hand, the results in the beer, cheese and snack crackers categories suggest that the reduction in these categories are driven by reduction at the retail level. As we discussed in Section 2, the way CKR propose to separate between their model and some of the alternatives, is by comparing overall high demand periods (like Christmas and Thanksgiving) to category specific peak demand periods (like Lent for tuna and cold for oatmeal). These results suggest that retailer behavior is driving the price reduction in categories that have expected peaks during periods of overall high demand, while retail behavior is not significant in those cases where the demand is category specific. This provides another piece of evidence that the loss-leader model might not be as relevant as CKR propose.

5. Detailed Analysis of Tuna

In this section we take a closer look at the canned tuna category. Later, in Section 5.3, we check if the results we find for tuna are also present in the other product categories. We focus on tuna for several reasons. First, this category seems to have the most robust results in support of the CKR loss leader model. It is the only category in Table 3 in which our results very closely reproduce the patterns found in CKR, and for which the patterns are present not only for the variable price index but also the fixed price index. Second, as CKR note, and as we discussed in Section 2, a key to separating the loss leader model from alternatives is to focus on products that have their own seasonal peak demand. The tuna category is probably the cleanest example of such an effect among the categories we focus on. Beer also has well defined idiosyncratic peak demand periods that are not overall peak demand periods. However, the results in Table 3 do not seem to support the loss leader story. Furthermore, the beer category in this data set is not representative of the US as a whole. In the national market Budweiser is a clear market leader, while in our data Miller has a larger market share. To the extent that the pricing decisions are impacted by other retailers and other markets, then this data set is not a good place to study the beer category.

5.1 *UPC-level price and quantity regressions*

In Table 5 we present brand level statistics for the top 30 UPC's in the tuna category. As we saw in Table 1, the combined market share of these products is roughly 90 percent. Each row presents results for a different UPC. In the fourth column we present the average price per ounce for each product. The distribution of prices is roughly bi-modal. For Lite Tuna, the prices range from 12 cents per ounce to 16 cents per ounce. White Tuna is more expensive, with prices ranging between 23 to 30 cents per ounce.

Columns (v)-(vii) present the UPC-level market shares during non-Lent periods, during Lent and the ratio of the two, respectively. The total overall quantity of tuna sold increases during Lent. So even some of the products that are losing market share are selling more during Lent. The products with a ratio of more than 0.7 are selling more during Lent, even if their market share is decreasing. The pattern is very clear: the quantity sold of light tuna increases during Lent, while there is no increase, even a slight decrease, in the quantity sold of the higher quality white tuna. This suggests that even within the tuna category there is a differential demand peak. Furthermore, it suggests that indeed a variable weight price index will tend to find a decrease in the price during Lent, even without any changes in prices.

Probably the most amazing statistic in Table 5 is the change in the market share of two products: Chicken of the Sea 6 ounce light tuna and 6 ounce light tuna in oil (rows 5 and 6). These two products almost triple their market shares during Lent. At the same time all other light tuna, including Star Kist 6.12 ounce cans of light tuna (rows 17 and 14) and Private Label 6.5 ounce cans (rows 10 and 12), the number 1 and 3-5 top-selling UPCs during non-Lent periods, are losing market shares. This difference could be driven by an exogenous increase in the demand for Chicken of the Sea (i.e., a change in brand preference) or by an endogenous increase in demand due to pricing or promotional activities.

The last columns in the table present results from separate UPC-level regressions. An observation in this regression is at the UPC-week level. In each regression retail price (or wholesale price or deal) is regressed on a Lent dummy variable and other holiday dummy variables. These regressions are identical to those used to produce the results in Table 3, but the dependent variable is the price of the UPC rather than a category price index. The table reports only the Lent coefficient and the robust standard error. A negative coefficient denotes a product that is systematically priced lower during Lent.

There are several patterns in these coefficients. First, in the light tuna category the products that have significant price decreases during Lent are products that are losing market shares (even despite the price reductions). The main two products gaining market shares do not have significant price decreases. Not only are the effects not statistically significant but the economic significance is small.[6] These results suggest that the increase in the market share we saw in columns (v)-(vii) is not driven by pricing.

Second, three out of the seven products with significant price reductions during Lent are white tuna, which we saw does not exhibit a seasonal shock.

Third, some of the wholesale prices seem to go down during Lent. However, there seems to be low correlation between the prices that exhibit reductions in wholesale prices and those that decrease the retail price. There are two ways to interpret these results. CKR claim that this is evidence in support of the claim that retailers behavior is driving pricing. Alternatively, these results could be driven by the poor quality of the wholesale prices. These prices are average acquisition cost, and so might poorly approximate the true economic marginal cost. Furthermore, these prices do not account for various agreements between the manufacturers and retailers, including promotional

[6]The price regressions are in levels and the dependent variables is measured in price per ounce. For brands 5 and 6 they suggest roughly a 2 cents decrease, for a 6 ounce can, which is normally priced around 80 cents. Approximately a 2.5% decrease.

agreements and coupons, and therefore potentially underestimate the effect of manufacturers.

Fourth, many of the UPCs that have increased advertising, as measured by the deal code, are those that are losing market share. Increased advertising is an application of the loss leader model.

Together, these patterns are not consistent with the loss-leader story. The products that are reducing their prices and increasing their advertising during Lent are not those that are facing an increase in demand, but rather those that are losing market share.

5.2 *UPC-level demand*

In this section we present results from a UPC-level demand model. The main purpose of this model is to further examine the pattern we saw in the last section. Analyzing the change in the quantity sold using a UPC-level demand system allows us to properly control for all of the changes in the market, including changes in prices and advertising.

The indirect utility for individual *i* from UPC *j* in week *t* is

$$u_{ijt} = x_{jt}\beta - \alpha p_{jt} + \xi_{jt} + \epsilon_{ijt},$$

where x_{jt} is a vector of observable characteristics, p_{jt} is the price of UPC *j* in week *t*, ξ_{jt} is an unobserved product characteristic, and ϵ_{ijt} is a mean zero stochastic term. The observable characteristics include the deal variable , UPC-level dummy variables, holiday dummy variables and interactions between the Lent dummy variable the UPC dummy variables, price and deal.

The individuals can also choose an "outside option" (i.e., none of the *J* products) that yields utility $u_{i0t} = \epsilon_{i0t}$. Assuming each individual chooses exactly one option and that ϵ_{ijt} is independently distributed with a Type 1 extreme value distribution, the market share of UPC *j* in week *t* is given by

$$s_{jt} = \frac{\exp(x_{jt}\beta - \alpha p_{jt} + \xi_{jt})}{1 + \sum_{k=1}^{J} \exp(x_{kt}\beta - \alpha p_{kt} + \xi_{kt})},$$

and the model can be estimated using

$$\log(s_{jt}) - \log(s_{0t}) = x_{jt}\beta - \alpha p_{jt} + \xi_{jt} \ .$$

The above model restricts the patterns of cross-price elasticities and therefore is inadequate for many purposes. However, our main focus are the interactions between the price and deal variables, and the Lent dummy variable. We expect the interaction to be significant. There is no reason to believe that the Logit model will yield qualitatively different results than alternative models that allow for more flexible substitution patterns.

Table 6 presents estimates from the Logit model. All the results were obtained using ordinary least squares. Different columns differ in the controls included in the regression. Column (i) presents results from a regression including only price (per ounce) and Holiday dummy variables. The next column presents the results from a regression that also includes UPC dummy variables. As expected, the price coefficient increases in magnitude. Before we include the UPC dummy variables there is a clear endogeneity problem: higher "quality" products might also be priced higher, therefore leading to a downward bias in the estimation of the price coefficient.

The results presented in column (iii) are from a regression that also includes an interaction between the Lent dummy variable and UPC dummy variables. For our purposes, the most important statistic from this regression is the p-value of the tests that all these interactions are equal to zero. In other words, the p-value of the test that the UPC dummy variables are the same during Lent and non-Lent periods. The hypothesis that the dummy variables are equal is rejected at the 2% significance level.

The hypothesis that the dummy variables are equal during Lent and non-Lent periods is rejected, at least at the 3% significance level, even once we control for additional variables in columns (iv)-(vii). This confirms the patterns we saw in Table 5. The relative demand for the different brands is changing, even once we control for pricing and advertising activities.

There are several other patterns in the table that are consistent with our story. In columns (iv), (vi) and (vii), we allow the price sensitivity to vary between Lent and non-Lent periods. We find that during Lent consumers are more price sensitive. This is consistent with our explanation.

In columns (v)-(vii) we add the deal code (i.e., advertising) to the regression. We find, in column (v) compared to column (iii), that the effect of advertising is positive and highly significant and that price sensitivity goes down. Both results are as expected. The decrease in price sensitivity is expected since many price reductions are joint with increased advertising activity, so not controlling for the direct effect of advertising would lead to over estimate the price sensitivity.

In the last two columns we allow the effect of the deal code to vary between Lent and non-Lent periods. We find that the interaction is not significant and we cannot reject the hypothesis that the effect is equal during the different periods. The loss leader story suggests that products in high demand are more likely to be advertised. Indeed CKR claim this as evidence in support of their model. As we claimed above, according to the loss-leader model, during peak demand periods the aggregate effect of bringing consumers to the store is much larger, since overall demand is higher. Therefore, the effect of advertising on brand-level demand should be larger during peak demand periods, which we do not observe in the results.

The above results were estimated using ordinary least squares. In principle, the estimates might be biased and inconsistent if the right-hand side variables are correlated with the error term. The regressions include UPC dummy variables, which control for any unobserved product characteristics that do not vary over time. The regressions also include holiday dummy variables, and in some cases the Lent dummy variable interacted with UPC-level dummy variables. Therefore, the error term captures variation within a UPC within a holiday. Besides random noise, which is not a problem, the error might also include the effect of unobserved promotional activity. The regressions include the deal code variable, but one could imagine that this variable is either measured with error or does not fully account for all the promotional activity. It is not hard to imagine that this unobserved promotional activity is correlated with price, and maybe even with the holiday dummy variables, Lent in particular. In this case the estimates will be biased.

There are several ways to deal with this problem. First, one could claim (and hope) that while the aforementioned correlation is theoretically possible, it is not a serious concern in the data. This is the argument made by CKR. If correct, the above results are unbiased. Alternatively, one could use instrumental variable methods to obtain consistent estimates.

We explore the second alternative. Table 7 presents estimates of the Logit model using the average acquisition cost as an instrumental variable for the price, interacted with the Lent dummy variable whenever appropriate. Thought of as the wholesale price, there are clear reasons why the average acquisition cost should be correlated with the retail price. Indeed, in the "first stage regressions" the excluded instruments are significant at the 0.1% significance level. It is less obvious why this variable will be uncorrelated with the error-term. If the unobserved promotional activity, which is captured by the error term, is set (unexpectedly) after the wholesale price is set then the average acquisition cost will be a valid instrument. However, if the unobserved promotion is set in coordination with the wholesale price, or if the wholesale price is set with some expectation with regards to the promotional activity, then wholesale price will not be a valid instrumental variable. We note that the average acquisition cost is not the current wholesale price but a weighted average of the current and past wholesale prices. Therefore, we might think that it is less likely to be correlated with the current promotional activity.

The columns of Table 7 present results from the same equations as the equivalent columns in Table 6, computed using two stage least squares. Comparing the two tables sheds some light on the importance of controlling for potential correlation with the error-term. With the exception of column (i), using two-stage least squares makes a difference. The fact that the results in column (i) are essentially identical are encouraging: the instrument surely is not valid before we control for the UPC-level dummy variables. In columns (ii)-(vii) the effects are almost identical. The price coefficient drops, in absolute value, by roughly a third compared to Table 6. The coefficient on the interaction of price and Lent doubles in magnitude. The coefficient on deal increases somewhat, but not in an economically significant way. The interaction of deal and Lent is still negative, roughly four times larger and statistically significant. This is consistent with our earlier descriptive analysis that products that lose market share are the ones advertising during Lent. Overall, our conclusions from Table 6 are supported and even made stronger.

In order to address some of the concerns we raised with our instruments, we also computed similar regressions using the lags of the acquisition costs as instrumental variables. The results were essentially the same. We do not address the potential correlation of deal with the error term, in any of these cases. We do not feel like we had an appropriate instrumental variable.

5.3 *Robustness and Additional Products*

While the previous two sections provided evidence that is consistent with our explanation, the analysis focused on a single product. We tried to motivate why we chose this product, nevertheless the generality of the results remains a question. In order to address this question we repeated the demand analysis discussed in the previous section for all the products. The results of OLS estimation of the Logit model are presented in Table 8. The results were computed by aggregating across stores.

At the bottom of the table, we present the p-value of the joint test that the interactions of UPC dummy variables and periods of expected high demand are equal to zero. As was the case for tuna during Lent, we find, for three of the four products, that the interaction of UPC level dummy variables and the periods of expected high demand are statistically significant. The exception is the beer category that, as we show above, does not seem to exhibit price reductions during the periods of high demand. Indeed, if we repeat the test only for those periods of expected high demand for which we found price reductions, the interactions are significant at standard levels.

Next, we explore the interaction of price and dummy variables for each holiday. The results are presented in the first column for each category of Table 8. Eight out of the eleven expected high demand periods in the table are negative. A negative interaction implies that demand is becoming more price sensitive and provides a rationale for price drops. However, many of these interactions are not statically significant. Recall that many of the expected high demand periods did not exhibit significant drops in the fixed weights price index. Therefore, the drop in the average price for these periods is explained by substitution towards cheaper brands, a composition effect, and we do not need a change in price sensitivity to explain the reduction in the average price paid by consumers. For that reason we highlight in bold type the six periods that exhibit a significant decline in the fixed price index during expected periods of high demand. All these interactions are negative and half of them are statistically significant. Overall, this provides support for our explanation, although somewhat weaker than the results for tuna presented in the last section.

Our demand results seem to be robust to functional form assumptions. CKR also present demand estimates. They study a constant elasticity demand at the category level, aggregating across the different brands. Their results are similar to ours. Like us, they find that demand for many products is more elastic during periods of high expected demand. They use these results to examine the Warner-Barsky theory. Therefore, they focus on the interactions with the Thanksgiving and Christmas dummy variables for all products, as these are periods of overall high demand. Our explanation, on the other hand, suggests focusing only on the periods of idiosyncratic peak demand. Hence, despite getting essentially the same results, we interpret them differently.

The second column for each category of Table 8 examines the interaction of the *deal* variable and the expected periods of high demand. As we previously discussed, according to the loss leader model, we expect demand to be more responsive to advertising during these periods. The results show that except for three cases, the effect of advertising is not higher during the expected periods of high demand, supporting the same result we found in the tuna category.

We repeat the analysis using Two Stage Least Squares instead of OLS. As we discussed above, we use the average acquisition price as the instrumental variables. The results are presented in Table 9. The results suggest that while controlling for endogeneity affects the coefficients, much like it did for tuna, the qualitative conclusions do not change much from those obtained from OLS.

6. Conclusions

In this paper we re-examine an empirical puzzle: why do prices go down during peak demand periods? We offer an explanation that is based on a change in the relative demand for different brands and a change in price sensitivity. Our empirical analysis offers results in support of our explanation and evidence that is not consistent with the alternative loss leader model.

In support of our explanation, we find that the reduction in a fixed weights price index is much smaller than the reduction in the variable weight price index, which is consistent with a change in the composition of brands and a substitution towards cheaper brands. We also find that in the tuna category the brands that face the highest increase in demand are not the ones reducing their prices. Instead, it is those brands that are losing market share that reduce their prices. Finally, estimates of brand-level demand for tuna suggest that changes in brand preferences are statistically significant and that the price sensitivity is higher (in absolute value) during Lent.

There are several ways in which our findings are inconsistent with the loss leader model. First, we find that the effects on fixed price indices are less significant, both economically and statistically, than the effects on variable price indices. For those categories (like tuna and oatmeal) that CKR claim are the key to separating their model from alternatives we find that wholesale prices play an important role in the price reductions. Second, examining the tuna category more carefully we find that not all brands face the same increase in demand and that those brands that face the higher increase are not the ones reducing their prices (or increasing advertising). Finally, we find that advertising is not more effective in increasing demand during periods of peak demand, contrary to the prediction of the loss-leader model.

The explanation we provide seems to be consistent with the data we examine. We do not claim that our explanation is the only reason for price reductions, or even that it is the only reason for price reduction during peak seasonal demand. More likely it is working jointly with some of the other effects like those offered by the Rotemberg Saloner (1986) theory, the Warner Barsky (1995) model, or the loss leader story.

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Table 1: Summary Statistics

	Tuna		Beer		Cheese		Snack Crackers		Oatmeal	
Variable:	**mean**	**s.d**	**mean**	**s.d**	**mean**	**s.d**	**mean**	**s.d**	**mean**	**s.d**
Retail Price Index (¢/oz)	15.45	0.86	4.87	0.16	14.95	1.16	21.79	1.87	15.59	1.27
Wholesale Price Index (¢/oz)	11.20	0.54	4.11	0.12	10.19	0.43	16.11	0.96	11.96	0.92
Margin (%)	26.65	4.25	14.21	2.28	25.13	3.89	25.42	3.83	22.64	5.55
Quantity (000's lbs)	614.72	414.39	5354.33	1861.37	1132.34	437.07	466.98	158.16	557.12	312.99
Units (000's)	88.96	68.14	29.74	9.08	130.41	49.48	41.65	13.46	28.81	19.78
Deal (%)	22.74	12.12	27.43	9.07	19.24	10.00	25.65	16.28	10.75	14.88
Quantity Share (%)	94.76	2.37	75.02	6.23	44.74	7.53	54.79	5.44	86.08	3.50

The retail and whole price index are computed using fixed weights, and averaged across stores and products within a week. Quantity and units, both measured in thousands, are summed over all stores and products within a week. The quantity share is the share of the UPCs used in the analysis out of the total quantity sold in the category.

Table 2: Seasonal Demand Peaks

	Tuna	Beer	Cheese	Snack Crackers	Oatmeal
Cold	8.99**	-12.95	2.91	2.18**	**11.60****
	(2.86)	(7.62)	(2.33)	(0.62)	**(3.99)**
Hot	3.90*	**89.25****	-0.93	-0.48	-6.55**
	(1.79)	**(10.93)**	(2.14)	(0.68)	(1.94)
Lent/Superbowl	**400.76***	**1582.82***			
	(158.19)	**(619.68)**			
Easter	-11.63	-195.13	290.56**	29.75	-101.20*
	(52.19)	(160.79)	(99.29)	(26.79)	(47.59)
Memorial Day	-99.95**	**2328.99****	335.13*	1.94	-66.78**
	(30.06)	**(656.42)**	(141.28)	(32.53)	(23.39)
July 4th	-63.82	**3060.81****	300.51*	25.29	-28.82
	(33.64)	**(932.14)**	(118.38)	(21.05)	(17.81)
Labor Day	-69.77*	**992.10**	257.42*	40.07*	242.94
	(32.15)	**(592.70)**	(107.69)	(17.36)	(147.88)
Thanksgiving	-154.82**	292.09	**456.85***	**186.10****	48.51
	(42.41)	(328.06)	**(176.89)**	**(65.56)**	(58.79)
Post Thanksgiving	-244.21**	1244.81*	-73.80	-15.05	-168.29**
	(76.33)	(615.58)	(171.71)	(39.95)	(47.97)
Christmas	-259.47**	**1564.01****	**705.91****	**349.00****	37.02
	(80.24)	**(434.25)**	**(166.09)**	**(41.63)**	(108.02)
Constant	650.53**	1905.74	1087.32**	526.29**	458.69**
	(58.42)	(998.97)	(57.06)	(17.98)	(118.73)

* Coefficient significantly different from zero at the 5% level.
** Coefficient significantly different from zero at the 1% level.
All columns report results from OLS regressions. The regressions also include a linear and quadratic time trend. The dependent variable in each column is the weekly quantity, measured in thousands of pounds, sold each week in each category. Bold type indicates period of expected high demand peaks. Robust standard errors are in parentheses.

Table 3: Seasonal Retail Price Changes: Category Price Indices

	Tuna		Beer		Cheese		Snack Crackers		Oatmeal	
	Fixed	**Variable**	**Fixed**	**Variable**	**Fixed**	**Variable**	**Fixed**	**Variable**	**Fixed**	**Variable**
Cold	-0.003	-0.02	-0.001	0.00	0.001	0.003	-0.02**	-0.02*	**-0.02***	**-0.03***
	(0.004)	(0.01)	(0.001)	(0.00)	(0.005)	(0.009)	(0.01)	(0.01)	**(0.01)**	**(0.01)**
Hot	-0.007	-0.009	**-0.004****	**-0.007****	-0.006	-0.001	0.001	0.03*	-0.01	-0.01
	(0.004)	(0.01)	**(0.001)**	**(0.002)**	(0.005)	(0.009)	(0.005)	(0.01)	(0.01)	(0.01)
Lent/	**-0.51****	**-1.78****	**-0.01**	**-0.04**						
Superbowl	**(0.19)**	**(0.47)**	**(0.07)**	**(0.08)**						
Easter	-0.45**	-0.38	0.05	0.07	-0.50*	-0.37	0.01	0.06	0.25*	-0.36
	(0.17)	(0.28)	(0.04)	(0.07)	(0.23)	(0.28)	(0.15)	(0.31)	(0.12)	(0.50)
Memorial Day	0.07	0.50	**-0.06**	**-0.15****	-0.63*	-0.55	-0.05	-0.09	0.26*	0.22
July 4th	(0.19)	(0.31)	**(0.03)**	**(0.05)**	(0.31)	(0.38)	(0.04)	(0.61)	(0.12)	(0.16)
	0.08	0.48	**-0.07**	**-0.27****	-0.71**	-0.61	-1.16**	-0.93*	0.05	-0.22
Labor Day	(0.18)	(0.32)	**(0.04)**	**(0.08)**	(0.25)	(0.38)	(0.31)	(0.38)	(0.13)	(0.15)
	-0.08	0.58	**0.03**	**-0.19***	-0.19	-0.48	-0.76*	-1.29*	-0.80	-0.85
Thanksgiving	(0.16)	(0.31)	**(0.04)**	**(0.08)**	(0.30)	(0.36)	(0.24)	(0.35)	(0.56)	(0.71)
	0.27	0.91*	-0.10	-0.04	**0.59**	**1.79**	**-1.22****	**-1.24****	0.04	0.14
Post Thanks	(0.14)	(0.25)	(0.06)	(0.06)	**(0.83)**	**(2.21)**	**(0.37)**	**(0.40)**	(0.35)	(0.33)
	0.27	0.67	-0.13*	-0.16	-0.64**	-0.85**	-1.33**	-1.33**	0.27	0.74**
Christmas	(0.17)	(0.59)	(0.06)	(0.12)	(0.13)	(0.28)	(0.38)	(0.40)	(0.18)	(0.20)
	0.19	0.86*	**-0.15****	**-0.12**	**-0.64***	**-1.14****	**-1.68****	**-2.35****	-0.08	-0.70
Constant	(0.13)	(0.41)	**(0.05)**	**(0.07)**	**(0.27)**	**(0.39)**	**(0.25)**	**(0.38)**	(0.37)	(0.53)
	15.43**	14.69**	4.59**	4.89**	14.75**	14.73*	18.74**	18.41**	13.55**	13.36**
	(0.11)	(0.25)	(0.09)	(0.14)	(0.17)	(0.29)	(0.12)	(0.19)	(0.41)	(0.57)

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

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

All columns report results from OLS regressions. The regressions also include a linear and quadratic time trend. The dependent variable in each column is the weekly price index for each category. Price is measured in cents per ounce. In columns titled *Fixed* and *Variable*, the price index is a fixed and variable-weight index, respectively. Bold type indicates period of expected high demand peaks. Robust standard errors are in parentheses.

Table 4: Seasonal Changes in Markups

	Tuna		**Beer**		**Cheese**		**Snack Crackers**		**Oatmeal**	
	Fixed	**Variable**	**Fixed**	**Variable**	**Fixed**	**Variable**	**Fixed**	**Variable**	**Fixed**	**Variable**
Cold	-0.002	-0.014	-0.001	-0.002	0.004	0.005	-0.01*	-0.01*	**-0.01**	**-0.02**
	(0.004)	(0.007)	(0.01)	(0.001)	(0.004)	(0.008)	(0.005)	(0.006)	**(0.01)**	**(0.02)**
Hot	-0.012 **	-0.014*	**-0.002***	**-0.004****	-0.007	-0.006	-0.009*	0.007	0.004	0.003
	(0.004)	(0.006)	**(0.001)**	**(0.001)**	(0.005)	(0.007)	(0.004)	(0.007)	(0.007)	(0.009)
Lent/	**-0.22**	**-0.69****	**-0.03**	**-0.13****						
Superbowl	**(0.12)**	**(0.22)**	**(0.08)**	**(0.09)**						
Easter	-0.44*	-0.48*	0.001	0.03	-0.10	-0.11	0.02	0.02	0.20*	0.13
	(0.18)	(0.23)	(0.03)	(0.05)	(0.21)	(0.32)	(0.17)	(0.23)	(0.12)	(0.18)
Memorial Day	-0.19	-0.01	**-0.10****	**-0.22****	-0.24	-0.63	-0.08	0.07	0.25*	0.27
July 4^{th}	(0.14)	(0.18)	**(0.03)**	**(0.03)**	(0.28)	(0.47)	(0.25)	(0.30)	(0.14)	(0.15)
	0.19	0.35	**-0.05**	**-0.14****	-0.32*	-0.59	-0.56*	-0.30	0.01	-0.08
Labor Day	(0.15)	(0.20)	**(0.05)**	**(0.06)**	(0.18)	(0.32)	(0.27)	(0.30)	(0.15)	(0.13)
	-0.09	0.10	**0.03**	**-0.09**	-0.16	-0.48	-0.81*	-1.15**	-0.41	-0.51
Thanksgiving	(0.09)	(0.14)	**(0.02)**	**(0.04)**	(0.22)	(0.37)	(0.24)	(0.34)	(0.47)	(0.58)
	0.33	0.46*	-0.06	-0.16	**0.52**	**1.79**	**-0.89****	**-1.09****	0.08	0.12
Post Thanks	(0.18)	(0.21)	(0.05)	(0.09)	**(0.90)**	**(2.34)**	**(0.29)**	**(0.35)**	(0.16)	(0.35)
	0.25	0.31	-0.09**	-0.16**	-0.58**	-0.74*	-0.96**	-1.08**	0.27	0.56
Christmas	(0.22)	(0.31)	(0.05)	(0.09)	(0.14)	(0.35)	(0.36)	(0.41)	(0.31)	(0.36)
	0.19	0.35*	**-0.10****	**-0.15****	**-0.61****	**-0.95****	**-1.15****	**-1.68****	0.14	0.05
Constant	(0.16)	(0.25)	**(0.04)**	**(0.05)**	**(0.21)**	**(0.35)**	**(0.25)**	**(0.33)**	(0.26)	(0.29)
	4.47**	3.88**	0.70**	1.25**	4.68**	4.45**	4.48**	4.40**	1.86**	2.06**
	(0.10)	(0.14)	(0.08)	(0.11)	(0.15)	(0.28)	(0.12)	(0.15)	(0.32)	(0.40)

* Coefficient significantly different from zero at the 5% level. ** Coefficient significantly different from zero at the 1% level.

All columns report results from OLS regressions. The regressions also include a linear and quadratic time trend. The dependent variable in each column is the weekly markup index for each category. Markup is price minus average acquisition cost, both measured in cents per ounce. In columns titled *Fixed* and *Variable*, the index is a fixed and variable-weight index, respectively. Bold type indicated period of expected high demand peaks. Robust standard errors are in parentheses.

Table 5: UPC-Level Anaylsis

Description				mkt share (%)			price regression		wholesale regression		deal regression	
#	brand	size (oz)	price (¢/oz)	non - Lent	Lent	ratio	Lent	s.e	Lent	s.e.	Lent	s.e.
Lite Tuna												
1	BB	6.12	13	3.7	3.2	0.86	-.22	.47	-.32	.28	-.04	.08
2	BB	6.12	13	13	10.2	0.78	-.29	.47	-.15	.21	.11	.09
3	BB	12.5	13.5	0.8	0.4	0.48	-.19	.16	-.22*	.13	.07	.12
4	COS	6.5	15.4	1.3	0.6	0.44	.22	.20	-.03	.10	.15	.10
5	COS	6	13.3	3.2	9.2	2.88	-.32	.46	-.51	.40	-.05	.09
6	COS	6	13.4	11.5	31.9	2.79	-.33	.46	-.70*	.42	-.11	.08
7	COS	12.5	14	0.9	0.4	0.47	.11	.20	.00	.14	.10	.09
8	COS	12.5	13.9	2.4	1.1	0.47	-.05	.19	.11	.14	.13	.09
9	COS	9.25	14	1.4	0.8	0.58	-.63**	.32	.05	.12	.18*	.10
10	PL	6.5	11.7	3.6	2.1	0.58	-.57	.40	.00	.23	.00	.11
11	PL	12.5	12.7	1.7	0.7	0.41	.11	.18	.09*	.05	-.03	.05
12	PL	6.5	11.6	6.5	4.3	0.66	-.47*	.27	-.04	.20	.15*	.09
13	SK	12.5	14.9	2.1	1.0	0.51	-.27	.20	-.11	.16	.14*	.07
14	SK	6.12	13.2	5.6	4.3	0.77	-.85*	.50	-.29*	.16	.16	.09
15	SK	9	15.4	1.5	0.9	0.57	-.31	.33	.01	.15	.31***	.09
16	SK	3.25	16.1	1.7	1.0	0.59	-.48	.30	-.27	.47	.10	.07
17	SK	6.12	13.2	18.3	16.1	0.88	-.97*	.50	-.30	.20	.13	.09
White Tuna												
18	3- D	6	24.8	2.5	1.6	0.65	-.28	.25	-.20	.38	-.09	.06
19	BB	6.12	29.6	0.7	0.3	0.51	.06	.16	-.99**	.52	.09	.11
20	BB	6.12	27.9	2.5	1.5	0.59	-.20	.27	-.63**	.31	.19**	.09
21	BB	9.2	28.9	0.5	0.2	0.42	.37**	.19	-.07	.15	-.10	.09
22	BB	6.12	22.5	1.9	1.1	0.59	-1.46***	.56	-.20	.41	.18**	.09
23	BB	12.2	27.5	1.3	0.7	0.58	-.31	.20	-.06	.14	.28***	.10
24	COS	6	27.1	1.8	1.0	0.56	-.76**	.37	-.19	.29	.30***	.10
25	GEIS	6	24.2	3.5	2.0	0.57	-.22	.18	.21	.19	.18*	.10
26	GEIS	13	22.4	1.3	0.7	0.54	-.33**	.14	-.10	.14	.04	.09
27	PL	6	24.2	0.9	0.4	0.43	.04	.14	-.11	.10	.07	.08
28	SK	9.75	25.9	0.6	0.3	0.55	-.09	.22	-.00	.14	.11	.08
29	SK	6.12	28.3	2.4	1.5	0.61	-.26	.22	.56*	.29	.08	.09
30	SK	6.12	25.8	1.1	0.6	0.50	-.16	.12	-.06	.18	.10	.08

* Coefficient significantly different from zero at the 10% level. ** Coefficient significantly different from zero at the 5% level. *** Coefficient significantly different from zero at the 1% level.

BB = Bumble Bee; COS = Chicken of the Sea; PL = Private Label; SK = StarKist; 3-D = 3 Diamonds; GEIS = Geisha

Numbers in the columns labeled *price regression*, *wholesale regression*, and *deal regression*, are the coefficient of the Lent dummy variable in separate regressions for each UPC where the dependent variables are retail price, average acquisition cost and the deal variable. These regressions also include other holidays dummy variables and trend variables, as in Tables 2 - 4. The columns labeled *s.e.* report the robust standard error from these regressions.

Table 6: Demand Estimates – OLS Results

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
price	-5.09	-22.07	-21.98	-21.23	-18.67	-17.82	-17.82
	(0.18)	(0.79)	(0.78)	(0.80)	(0.88)	(0.90)	(0.90)
lent*price				-7.08		-8.36	-8.36
				(2.76)		(3.06)	(3.06)
deal					0.28	0.29	0.29
					(0.03)	(0.03)	(0.03)
deal*lent						-0.12	-0.12
						(0.09)	(0.09)
UPC dummies		✓	✓	✓	✓	✓	✓
UPC dummies*lent			✓	✓	✓	✓	✓
p-value of all UPC dummies *lent = 0			0.02	0.02	0.03	0.02	0.02
Holiday dummies[a]	✓	✓	✓	✓	✓	✓	

Estimates from OLS regressions. The dependent variable is $\log(s_{jt}/s_{0t})$. A market is defined as a week, by aggregating across all the stores. There are 340 markets with 9495 observations. In addition to the above variables all regressions include a linear and quadratic time trend and a Lent dummy variable. Robust standard errors are given in parentheses.

[a] Dummy variables for Lent, Easter, Memorial Day, July 4th, Labor Day, Thanksgiving, Post Thanksgiving, Christmas, Hot and Cold.

Table 7: Demand Estimates – IV Results

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
price	-4.82	-15.38	-15.15	-12.80	-10.97	-7.86	-7.86
	(0.19)	(1.76)	(1.72)	(1.69)	(2.07)	(2.07)	(2.07)
lent*price				-20.55		-26.19	-26.19
				(5.42)		(6.13)	(6.31)
deal					0.41	0.46	0.46
					(0.04)	(0.04)	(0.04)
deal*lent						-0.45	-0.45
						(0.15)	(0.15)
UPC dummies		✓	✓	✓	✓	✓	✓
UPC dummies*lent			✓	✓	✓	✓	✓
p-value of all UPC dummies *lent = 0			<0.01	<0.01	<0.01	<0.01	<0.01
Holiday dummies[a]	✓	✓	✓	✓	✓	✓	

Estimates from Two Stage Least Squares regressions, using wholesale price as an instrument (interacted with lent where appropriate). The dependent variable is $\log(s_{jt}/s_{0t})$. A market is defined as a week, by aggregating across all the stores. There are 340 markets with 9495 observations. In addition to the above variables all regressions include a linear and quadratic time trend and a Lent dummy variable. Robust standard errors are given in parentheses

[a] Dummy variables for Lent, Easter, Memorial Day, July 4th, Labor Day, Thanksgiving, Post Thanksgiving, Christmas, Hot and Cold.

Table 8: Demand Estimates – OLS Results

	Beer		Cheese		Snack Crackers		Oatmeal	
Price/Deal	-57.82**	0.48**	-5.35**	0.43**	-5.10**	0.42**	-11.10**	0.46**
	(2.58)	(0.03)	(0.53)	(0.02)	(0.48)	(0.02)	(0.53)	(0.03)
Interaction with:								
Cold							**-0.22****	**-0.008****
							(0.02)	**(0.002)**
Hot	**-0.02**	**-0.001**						
	(0.20)	**(0.002)**						
Superbowl	10.07**	0.17**						
	(3.61)	(0.08)						
Memorial Day	-4.02	0.03						
	(10.26)	(0.11)						
July 4th	8.42	0.23						
	(12.62)	(0.16)						
Labor Day	-0.40	0.32**						
	(9.23)	(0.13)						
Thanksgiving			0.71	0.32*	**-3.18****	**-0.09**		
			(0.83)	(0.15)	**(0.76)**	**(0.09)**		
Christmas	**-8.97**	**0.18**	**-0.19**	**-0.003**	**-2.75****	**-0.14****		
	(9.27)	**(0.12)**	**(0.27)**	**(0.06)**	**(0.48)**	**(0.05)**		
p-value of all UPC dummies *holiday = 0	0.40		<0.01		<0.01		<0.01	

Estimates from OLS regressions. The dependent variable is $\log(s_{jt}/s_{0t})$. A market is defined as a week, by aggregating across all the stores. In addition to the above variables all regressions include a linear and quadratic time trend, UPC dummy variables and holiday dummy variables. Bold type indicates period of expected high demand that showed a reduction in the fixed weights price index. Robust standard errors are given in parentheses.

Table 9: Demand Estimates – IV Results

	Beer		Cheese		Snack Crackers		Oatmeal	
Price/Deal	-47.94**	0.56**	-3.27**	0.49**	-3.66**	0.47**	-9.33**	0.52**
	(6.53)	(0.06)	(0.61)	(0.02)	(0.81)	(0.03)	(0.53)	(0.04)
Interaction with:								
Cold							**-0.28****	**-0.011****
							(0.05)	**(0.003)**
Hot	**0.35**	**0.002**						
	(0.45)	**(0.004)**						
Superbowl	10.76**	0.18**						
	(4.04)	(0.08)						
Memorial Day	-7.17	-0.03						
	(19.71)	(0.16)						
July 4th	8.23	0.23						
	(20.91)	(0.21)						
Labor Day	-19.04	0.16						
	(19.29)	(0.21)						
Thanksgiving			0.09	0.23**	**-2.11***	**-0.05**		
			(0.31)	(0.10)	**(1.00)**	**(0.09)**		
Christmas	**9.23**	**0.88****	**0.13**	**0.03**	**-1.45****	**-0.20****		
	(31.15)	**(0.28)**	**(0.40)**	**(0.10)**	**(0.54)**	**(0.06)**		
p-value of all UPC dummies *holiday = 0	0.16		<0.01		<0.01		<0.01	

Estimates from Two Stage Least Squares regressions, using wholesale price as an instrument (interacted with lent where appropriate). The dependent variable is $\log(s_{jt}/s_{0t})$. A market is defined as a week, by aggregating across all the stores. In addition to the above variables all regressions include a linear and quadratic time trend, UPC dummy variables and holiday dummy variables. Bold type indicates period of expected high demand that showed a reduction in the fixed weights price index. Robust standard errors are given in parentheses.