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# Why Don't Prices Rise During Periods of Peak Demand?

## Evidence from Scanner Data

By JUDITH A. CHEVALIER, ANIL K KASHYAP, AND PETER E. ROSSI\*

*We examine retail and wholesale prices for a large supermarket chain over seven and one-half years. We find that prices fall on average during seasonal demand peaks for a product, largely due to changes in retail margins. Retail margins for specific goods fall during peak demand periods for that good, even if these periods do not coincide with aggregate demand peaks for the retailer. This is consistent with "loss-leader" models of retailer competition. Models stressing cyclical demand elasticities or cyclical firm conduct are less consistent with our findings. Manufacturer behavior plays a limited role in the countercyclicality of prices. (JEL L13, E32, L81)*

In a standard perfectly competitive model of price determination, positive demand shocks result in either no change or an increase in prices. There is a growing body of evidence that retail prices do not obey the standard model and that prices fall in periods of high total demand. Elizabeth J. Warner and Robert B. Barsky (1995) provide evidence that prices of consumer appliances fall in the Christmas holiday period.

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James M. MacDonald (2000) studies grocery prices and finds many items whose price declines in periods when the total quantity purchased is high. The goal of this work is to more rigorously document this finding with actual transactions data and, more importantly, to explain why this might occur. We examine three theories of imperfect competition, all of which can produce countercyclical prices and develop an empirical strategy for discriminating between these theories.

Our tests are based on a unique data set taken from a large supermarket chain in the Chicago area. There are several reasons for looking at supermarket data. First, the grocery-retailing sector is huge, with sales totaling \$435 billion in 1999, accounting for 25 percent of nondurable retail sales. Second, the consumer-retailer interactions mimic conditions present in many other types of purchases (e.g., purchases are frequent and small relative to search costs), making the patterns that we uncover potentially relevant for other parts of the economy.

The most important reason for focusing on supermarkets, however, is that several novel aspects of our data set allow us to overcome measurement problems that have plagued previous studies of price-cyclicality in imperfectly competitive markets. One advantage of our data set is the availability of a very accurate time series on the *transaction* prices of thousands of goods. Second, we are able to observe *retail prices, quantities, and the wholesale prices* paid

by the supermarket, giving us a better-than-usual measure of the retailer's marginal cost and profit margins. Previous researchers have been forced to infer markup cyclicity using data on prices without direct measures of costs. Our wholesale price data allows us to determine if countercyclical pricing is primarily due to retailer or manufacturer behavior. In addition, information on price advertising is available which allows us to shed further light on the implications of theories of pricing which have a role for advertising. Finally, we exploit the fact that the demand for many supermarket goods follows a predictable seasonal or holiday cycle. The response of prices to these foreseeable demand shifts provides a method of discrimination between alternative theories of retailer and manufacturer competition.

We examine three classes of models based on imperfect competition that have been put forth in the literature to explain why markups may be countercyclical. First, we consider models in which demand elasticities are cyclical due to economies of scale in search (Warner and Barsky, 1995). Procyclical patterns of demand elasticities then produce countercyclical patterns of retail or manufacturer markups. The second class of models draws on the work of Julio J. Rotemberg and Garth Saloner (1986), who suggest that countercyclical markups could result from changes in the ability of firms to sustain implicit collusion in situations where demand is changing from period to period. Both the first and second class of models predict a fall in markups during periods of high aggregate demand. In the case of our supermarket data, these aggregate demand peaks occur during holiday periods. Thus, these theories predict a fall in retail markups during the Christmas holiday but have no prediction for the prices of goods whose demand idiosyncratically peaks during a period of low or average overall demand at the supermarket. Examples of an idiosyncratic demand increase include demand for canned seafood during Lent or the increase in beer demand during the summer.

Loss-leader models of advertising form the third class of models. In these models (exemplified by the work of Rajiv Lal and Carmen Matutes, 1994), retailers compete for customers via advertised prices. It is efficient for the retailer to advertise and discount items in high

relative demand. In the loss-leader style model, margin reductions occur on items at the time of highest demand for that item even if this does not coincide with a period of high aggregate demand.

Overall, our findings provide support for the loss-leader/advertising models of retail markups. The pattern of retailer markup variation that we observe appears to be inconsistent with retailer behavior being driven by the mechanisms described by either Rotemberg and Saloner (1986) or Warner and Barsky (1995). We supplement these findings by examining directly whether consumers are more price sensitive during peak demand periods. In general, we find that they are not, casting further doubt on cyclical demand elasticities as an explanation for the countercyclical pricing in our data. Finally, we provide explicit evidence that advertised goods are discounted at these seasonal peaks in demand. We also examine wholesale prices and find that reductions in wholesale price do occur at seasonal frequencies but the magnitude of these reductions is small relative to changes in retail markups. Thus, our work points to the importance of an active role by the retailer in setting and determining the seasonal or cyclical pattern of prices.

The rest of the paper proceeds as follows. In Section I, we describe the theoretical predictions to be tested. In Section II, we describe the data set and document important features of the supermarket retail environment. In Section III, we show evidence about the seasonality of supermarket prices. In Section IV, we examine retail margin behavior and its consistency with the theories of price fluctuations. Section V describes wholesale price changes. Section VI investigates the Warner and Barsky (1995) model more closely, reporting evidence on changes in the price sensitivity of purchases at peak demand period. Section VII investigates seasonal advertising patterns in an effort to further examine the loss-leader hypothesis. Section VIII concludes.

## I. Classes of Models and Empirical Implications

We will consider three classes of models that can generate countercyclical pricing: a model of countercyclical collusion, a model of cyclical elasticity of demand, and a model of loss-leader

advertising by multiproduct firms. All three of these models are potentially consistent with the basic observation that supermarket prices tend to fall on average during the seasonal demand peaks for a particular good. The goal of this section is to provide the fundamental economic intuition behind these three classes of models and to draw out their differing empirical predictions. A model Appendix, available at <http://gsbwww.uchicago.edu/fac/peter.rossi/research/>, provides a unified theoretical treatment of the models considered in this section.

#### A. *Economies of Scale in Search and Cyclical Demand Elasticities*

Mark Bills (1989) and Warner and Barsky (1995) both propose different mechanisms by which demand might be more elastic than usual during demand peaks, leading optimal markups to be countercyclical. The Bills (1989) model focuses on durable goods purchases and may be inappropriate to our particular setting. Warner and Barsky generate cyclical demand elasticities by modeling economies of scale in search. With fixed costs of search and travel between stores, it is optimal to search and travel more during high purchasing periods, when these fixed costs can be at least partially shared across purchases. This makes consumers more price-sensitive when overall demand is high. Consistent with their hypothesis, Warner and Barsky find evidence that prices for many consumer goods fall at Christmas and on weekends, periods when consumers are intensively engaged in shopping. In the context of supermarket products, the Warner and Barsky model might be applied to periods in which there is high aggregated demand such as the Christmas holidays. In these periods, the higher total market basket results in increased price search and travel for bulk buying, creating high demand elasticities and lower retail margins.

#### B. *Countercyclical Collusion Models*

Another class of models emphasizes dynamic interactions between firms. If retailers compete with one another repeatedly, tacit collusion may emerge. Rotemberg and Saloner (1986) consider tacit collusion in an environment with variable demand. The logic of these models is

simple: tacit collusion is sustainable when the gains from defection in the current period are low relative to the expected future cost of being punished for the defection. The temptation to cheat from a collusive arrangement is highest during a temporary demand spike, because the gain from cheating is increasing in current demand, while the loss from punishment increases in future demand. Severin Borenstein and Andrea Shepard (1996) find pricing behavior consistent with Rotemberg and Saloner's model at the seasonal frequency.

B. Douglas Bernheim and Michael D. Whinston (1990) extend this analysis to a multiproduct environment. While their focus is on conglomerates in multiple lines of business, their analysis extends directly to the case of the multiproduct retailer. The Bernheim and Whinston analysis shows that tacit collusion may lead markups to be lowered at points in the seasonal cycle where aggregate demand is high, but, holding aggregate demand fixed, idiosyncratic seasonality of individual goods should not affect the maintenance of tacit collusion.

#### C. *Loss-Leader Advertising Models*

The notion of a retailer using loss-leaders to compete for customers has a long informal tradition. For example, Robert L. Steiner (1973) argues that national TV and media advertising establishes brand identities. The existence of these branded products allow consumers to "compare prices between stores," creating scope for retailer competition. However, Steiner does not explicitly provide a role for *retailer-sponsored* price advertising as a way of competing for customers. Lal and Matutes (1994) provide a formalization of the Steiner argument as well as provide a role for retailer advertising. An important feature of the Lal and Matutes model is the assumption that consumers do not know the prices that are charged until they arrive at the store. This creates the following conundrum: once consumers arrive at the store there is some scope for the retailer to expropriate (through high prices) the consumer's sunk investment in traveling to the store. Foreseeing this hold-up problem, consumers will not go to the store.

The solution to this conundrum is price advertising. Advertising serves to commit the

retailer to charge particular prices. If advertising were costless, retailers would advertise all of the prices. In practice, however, advertising is not costless. We do not observe supermarkets, for example, advertising the prices of all of the goods that they sell. The typical supermarket circular advertises the prices of roughly 200 items, although the typical store carries on the order of 25,000 items. Lal and Matutes (1994) point out that, if the retailer only advertises a subset of the products, consumers will correctly infer that all unadvertised products are being sold for their reservation price. Lal and Matutes further assume that retailers pay an advertising cost per good advertised. They show that, if advertising costs are high enough, the sole equilibrium features one good being advertised, with the unadvertised good being sold at the consumers reservation price.

Although not highlighted in Lal and Matutes, with nonnegativity constraints on prices the model requires that the advertised very-low-priced items be items for which demand is relatively high. Thus, this model predicts it would be more efficient for retailers to advertise items that are relatively more popular. This prediction distinguishes this model from the countercyclical conduct and cyclical demand elasticities models because, in the loss-leader model, advertising and price reductions are geared to the level of demand for a particular item not the aggregate demand. In other words, an item-specific demand shift could trigger advertising and price reductions for that item.

This same intuition, that more popular goods are more likely to be advertised, holds true whether the increase in demand for a particular good occurs at the extensive or intensive margin. Our model Appendix shows this result for the intensive margin. Daniel Hosken et al. (2000) extend the Lal and Matutes model to illustrate that goods that are bought by a greater fraction of all consumers are more likely to be advertised.

Lal and Matutes do not consider manufacturer competition in their model. Lal and J. Miguel Villas-Boas (1998) provide an extension of the model to include manufacturer as well as retailer competition. In the Lal and Villas-Boas paper, there are regions of the parameter space in which the equilibrium can be interpreted as a loss-leader equilibrium.

There are other explanations for “loss-leader” retail pricing. For example, Kyle Bagwell (1987) provides a role for “introductory” prices as a signal of the cost type of a firm. In Duncan Simester (1995) advertised prices are somewhat informative about unadvertised prices, as only low-cost firms advertise very low prices.

Finally, we should note that Lal and Matutes do not consider reputation effects that might occur in repeated games. Reputational concerns might prevent retailers from expropriating the consumer’s investment in traveling to the store. Consumers are probably quite well informed about the prices of essential items such as meat, produce, and dairy but likely are far from perfectly informed about the prices of seasonal items. Thus, for the seasonal products that we study, the loss-leader mechanism identified by Lal and Matutes could be more important than for everyday essential items.

#### D. Increasing Returns

We do not consider increasing returns to scale, although these could explain falling prices during demand peaks. It is important to distinguish between three types of increasing returns to scale: (1) overall increasing returns to scale at the retailer level, (2) scale economies for retailers stemming from increases in the sales of particular items, and (3) increasing returns to scale at the manufacturer level. These different forms of increasing returns to scale would have different implications for the pricing behavior we examine.

The first version, overall increasing returns to scale at the retailer level, would be observationally equivalent to the Warner and Barsky (1995) (hereafter, W-B) mechanism and the Rotemberg and Saloner (1986) (hereafter, R-S) mechanism. We find it unlikely that this type of increasing returns is important in our data for three reasons. First, and most importantly, it seems most likely that increasing returns at the retailer level will stem from fixed cost savings. Fixed cost savings should not affect optimal pricing fluctuations at the seasonal frequency; fixed costs only affect pricing when they affect the number of competitors in the market, a mechanism not plausible at the seasonal frequency. Second, while marginal cost savings during seasonal demand peaks are theoretically plausible, it is

difficult to pinpoint what mechanism would drive such cost savings. Finally, as we detail later, we find that, if anything, overall prices at the supermarket appear to be rising at the biggest overall demand peaks, Thanksgiving and Christmas. Given the measurement problems involved in this exercise we do not want to overemphasize this result, but it is contrary to what would be expected if this type of increasing returns were present.

The second type, increasing returns to scale for a particular item, would be observationally equivalent to the Lal and Matutes (1994) (hereafter, L-M) mechanism. This stands in contrast to increasing returns to scale *overall* at the retailer level, because the latter does not imply falling prices for goods experiencing idiosyncratic demand shifts. We will return to the plausible magnitudes of these cost savings from this second type of increasing returns when we review the pricing results.

The third type, increasing returns to scale for manufacturers, would be, with our data, observationally indistinguishable from price drops due to falling manufacturer margins. Since we find in our empirical analysis that price decreases at seasonal peaks are largely due to retailer behavior, we do not devote consideration to this third possibility.

### E. Empirical Implications

All of the models discussed above predict that the prices of high-demand goods will fall during high-demand periods. The theories differ, however, in their predictions for demand elasticities, and for the behavior of retailer margins for high-demand goods during periods of overall low demand. The loss-leader models predict that retailer margins will fall for high-demand goods even if the demand increase for that good is totally idiosyncratic. They also predict an increase in advertising during these episodes.

Neither the R-S model nor the W-B model predict that overall retailer margins will fall during these idiosyncratic demand peaks. However, applying the logic of either model to competition among manufacturers may predict that *manufacturer* margins will fall during product-specific demand peaks. That is, for example, we might expect that R-S would predict that tuna

manufacturers will compete fiercely during Lent, a seasonal spike in demand for tuna. One could similarly tell a within-store variant of the W-B model and predict that consumers will be more elastic across brands of tuna during Lent, causing manufacturers to lower markups.

## II. Data Description and Seasonality of Demand

Dominick's Finer Foods (DFF) is the second-largest supermarket chain in the Chicago metropolitan area; they have approximately 100 stores and a market share of approximately 25 percent. Dominick's provided the University of Chicago Graduate School of Business with weekly store-level scanner data by universal product code (UPC) including: unit sales, retail price, profit margin (over the wholesale price), and a deal code indicating that the price reduction is accompanied by some sort of advertising (typically a feature ad or special shelf tag). This UPC-level database does not cover all items that DFF sells; only certain categories of products are available. The 29 categories available constitute approximately 30 percent of the dollar sales at DFF.

To complement the data on retail prices, we inverted DFF's data on profit per dollar of revenue that is contained in the database to calculate the chain's wholesale costs and retailer percentage margin [defined as  $(\text{price} - \text{cost}) / \text{price}$ ]. Note, however, that the wholesale costs that we can recover do not correspond exactly to the desired theoretical construct, the replacement cost of the item. Instead we have the average acquisition cost of the items in DFF's inventory. DFF generally knows that a trade deal is coming in advance of the first day of a deal. Our understanding is that optimal inventory management on DFF's part results in a trade deal being incorporated in the acquisition cost relatively quickly. Of greater concern is the fact that DFF may stock up its inventory during trade deals; this means that the acquisition cost may remain depressed for some time after a trade deal has expired.

In addition to the category-level data, DFF also provided data on total sales by department. We construct total sales by adding total sales from the grocery, produce, dairy, frozen foods, meat, fish, deli, bakery, and frozen meat departments. Sales from other departments are not

included due to missing data problems. Next, we calculate total sales per store day for each week. We use this measure rather than simply total sales to adjust for store openings, closings, and reporting problems.

The standard time period for our analysis are the 400 weeks starting with the week of September 14, 1989 (when the DFF relationship began). However, data collection began and ended at different times for some of the categories. All of the DFF data are publicly available, and can be found, along with a thorough description of the collection of the data, at <http://gsbwww.uchicago.edu/kilts/research/db/dominicks/>.

### A. Variable Construction

We supplement the data from DFF with information on weather and the dates of certain holidays. We measure weather-induced cycles by constructing two temperature variables. To construct these, we first obtained historical (hour by hour) weather data from the National Oceanic and Atmospheric Administration on Chicago temperatures—these data can be found at [www.noaa.gov](http://www.noaa.gov). From these, we calculated a mean temperature for each week of the year based on the historical data. This series appeared to be influenced by outliers, so we smoothed the weekly data to obtain a smooth seasonal temperature series, representing average seasonal patterns. We used this smoothed mean temperature (TEMP) series to generate two variables:

$$\begin{aligned}\text{HOT} &= \max(0, \text{TEMP} - 49) \\ \text{COLD} &= \max(0, 49 - \text{TEMP}).\end{aligned}$$

Forty-nine degrees Fahrenheit is approximately both the mean and median temperature in Chicago. Moreover, in addition to this parametric specification of changing weather conditions, we also experimented with using dummy variables to isolate the warmest (and coldest) six or eight weeks and found very similar results to those that we report here.

We also generated dummy variables that equal 1 in the shopping periods around each holiday. DFF's database contains weekly data in which the weeks commence on Thursday and end on Wednesday, the same period for which a store sales circular is typically active. Because

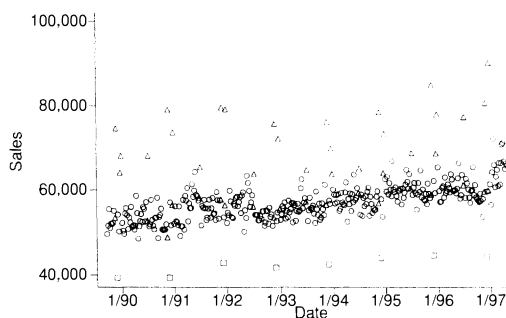


FIGURE 1. DFF SALES PER STORE DAY

*Notes:* Weekly values of sales per store day are graphed. Circles represent nonholiday weeks. Triangles represent Christmas, Thanksgiving, and July 4th weeks. Squares represent the week after Thanksgiving.

the day of week that different holidays might land on can vary across years, we generate a dummy variable that takes the value 1 for two shopping weeks before each holiday. For Thursday holidays, then, the variable was set to 1 for the two weeks prior to the holiday, but 0 for the week including the holiday. For holidays taking place on all other days, the dummy variable was set to 1 for the week before the holiday and for the week including the holiday. We allow the Christmas dummy to remain equal to 1 for the week following the holiday, since shopping in preparation of Christmas and shopping in preparation for New Year's will be very difficult to disentangle. We also construct a variable "Lent," which will be important later in our analysis of tuna sales. The religious season of Lent lasts for 40 days prior to Easter, so our Lent variable takes the value of 1 for the four weeks preceding the two-week Easter shopping period. Finally, we construct the variable "Post-Thanksgiving" which takes the value of 1 for the week following Thanksgiving.

### B. Seasonal Patterns in Total Sales

Total demand at Dominick's is extremely volatile around holidays. Figure 1 shows weekly sales per store day at the chain level. The two-week shopping periods preceding Christmas, Thanksgiving, and the Fourth of July are highlighted with squares. The week following Thanksgiving is highlighted with triangles. It is apparent that Christmas and

Thanksgiving represent the overall peak shopping periods for DFF, while the week following Thanksgiving represents the absolute trough.

The qualitative impression in Figure 1 can be confirmed via a regression of total sales per store day on a linear and quadratic time trend (to adjust for overall growth), our temperature variables, and dummies representing the shopping periods for Lent, Easter, Memorial Day, July 4th, Labor Day, Thanksgiving, the week following Thanksgiving, and Christmas. Statistically significant increases in total sales occur at Easter, Memorial Day, July 4th, Thanksgiving, and Christmas. However, the magnitudes of the revenue increases for Easter, Memorial Day, and July 4th are very small relative to Thanksgiving and Christmas. Neither the predictable changes in temperature, nor Lent are associated with aggregate spending surges. As seen in Figure 1, the week following Thanksgiving is characterized by a huge, statistically significant decline in sales.

### C. Selection of Categories

As discussed above, our data is organized into 29 different groups or categories of fairly homogenous products, e.g., snack crackers or canned soups. Since our goal is to examine the pricing of goods at times when they experience demand shocks, we identified a subset of our categories that, on a priori grounds, we believed would experience some sort of seasonal demand shifts. A summary of each category we considered on these a priori grounds and the expected peak demand periods are described in Table 1.

It is essential that our proposed demand shocks make sense to the reader on an a priori basis. If we are not certain that these quantity movements are at least partially driven by shifts of a demand curve, then we could be mistakenly uncovering movements along the demand curve because of changing prices. MacDonald (2000) takes a different approach, regressing quantity sold on monthly dummies for a wide variety of items, and then selecting items with large observed quantity peaks in a particular month. This approach could confound demand and supply shocks.

We complement our set of seasonal categories with categories in which we expect no seasonal demand shifts: analgesics, dish detergent, cookies,

TABLE 1—EXPECTED PERIODS OF PEAK DEMAND FOR DIFFERENT TYPES OF FOOD

| Category             | Expected demand peaks                                               | Comments                                                                                      |
|----------------------|---------------------------------------------------------------------|-----------------------------------------------------------------------------------------------|
| Beer                 | Hot weather<br><br>Memorial Day, July 4th, Labor Day, and Christmas | Holidays represent peak picnic times, and for Christmas includes the run-up to New Year's Eve |
| Canned eating soups  | Cold weather                                                        |                                                                                               |
| Canned cooking soups | Thanksgiving and Christmas                                          | Broths are a particular complement for turkey                                                 |
| Cheeses (nonsliced)  | Thanksgiving and Christmas                                          | This category consists of cooking cheeses and cheeses suitable for serving at parties         |
| Oatmeal              | Cold weather                                                        |                                                                                               |
| Snack crackers       | Thanksgiving and Christmas                                          |                                                                                               |
| Soft drinks          | Hot weather<br><br>Memorial Day, July 4th, Labor Day, and Christmas | Holidays represent peak picnic times, and for Christmas includes the run-up to New Year's Eve |
| Tuna                 | Lent                                                                | Many Christians abstain from eating meat during this religious period                         |

and regular crackers (which includes saltines, graham crackers, and oyster crackers). To check our a priori classification of categories, we calculate a crude measure of the seasonality. To do this, we regress total category-level quantity sold for each product on a linear and quadratic trend terms, the cold and hot variables, and the dummy variables representing the shopping periods for Lent, Easter, Memorial Day, July 4th, Labor Day, Thanksgiving, Post-Thanksgiving, and Christmas. We examine the incremental change in *R*-squared as the

seasonal variables are added to the regression as a measure of the seasonal nature of the category.

These regressions suggest some departures from our a priori classifications. Firstly, analgesics, one of our a priori nonseasonal categories, does, in fact, have a modest cold-weather seasonal. Secondly, as mentioned above, cookies appear to have a counter-holiday seasonal, with sales falling at Christmas. Finally, the hot weather seasonal for soft drinks was much smaller than we had anticipated. In fact, a closer inspection of the soft drinks data suggested to us a number of coding problems that lead us to exclude soft drinks from all of our subsequent analysis. But, overall, the predictions in Table 1 are borne out.

#### D. Construction of Items and Category Aggregates

Having selected categories for study, there are essentially two ways that one could proceed. First, one could study the behavior of individual UPCs or items within each category. Second, one could attempt to study category-level aggregate behavior. Both of these avenues have potential pitfalls.

Examining only a few individual UPCs could be misleading due to the multiproduct nature of the retailer's problem; retailers may choose to discount only one or a few items in a category (that is, if store traffic is driven by having some tuna on sale at Lent, not by having all tuna on sale). If this is so, the UPCs chosen for study by the econometrician could be highly nonrepresentative and could lead one to over- or underestimate the size of holiday and weather effects.

Examining category-level data is also problematic; small share items tend not to be stocked at all stores at all times. Trying to include all category members in a price index can lead to a price index that is not consistent over time. This is particularly challenging for our analysis because stores may well expand their offerings in a category during a peak demand period. For example, the cookie category contains several pfeffermuesse UPCs, but only at Christmastime.

For these reasons, we choose a hybrid approach. For each category in our study, we construct a list of the top-selling UPCs. We use this list to construct narrowly defined price aggregates within each category representing the

leading products in each category. So, for example, we constructed seven price aggregates for the tuna category. Each aggregate contains only those items that have extremely high price correlations with one another. For instance, Chicken of the Sea 6 oz. Chunk Lite Tuna in Oil and Chicken of the Sea 6 oz. Chunk Lite Tuna in Water have a price correlation of 1.000 in the data set. Thus, we move them into a single item aggregate. Depending on the category we are left with between 6 and 12 price aggregates, and these aggregates account for 30 to 70 percent of total category sales. For details, see the Data Appendix at <http://gsbwww.uchicago.edu/fac/peter.rossi/research/>.

#### E. Construction of Price Indices

All of our analyses involve some sort of aggregate index of retail price, wholesale price, or retail margin. The scanner data is collected at the store level for a given UPC. We must aggregate over both UPCs and stores to obtain a chain-level index that is then related to various seasonal variables. As discussed above, we conduct our analysis on two levels of product aggregation. First, we aggregate UPCs for very similar products to form "item" aggregates. The second part of our index procedure involves aggregating over these items to form a category-level index.

We use a current expenditure share-weighted average of the log prices to form a log price index. Let  $P_{ciust}$  be the price of UPC  $u$  (in standardized units such as ounces or pounds) of item  $i$  from category  $c$  in store  $s$  in week  $t$ . We form the item aggregates,  $P_{cit}$ , as follows:

$$P_{cit} = \sum_s \sum_{\forall u \in i} w_{ciust} \ln(P_{ciust})$$

where  $w_{ciust}$  is the dollar share of UPC  $u$  in store  $s$  in week  $t$ . In the second stage, aggregate over items to form a chain-level price index for category  $c$ .

$$P_{ct} = \sum_{\forall i \in c} w_{cit} P_{cit}$$

where  $w_{cit}$  is the dollar share of item  $i$  in category  $c$  at time  $t$ .

Our price indices use time-varying weights because of two features of our data. One is that the items are highly substitutable. The second is the common occurrence of temporary price discounts. A fixed-weight index will understate the effective change in price in the category since it will fail to account for the pronounced shifts in purchase patterns towards the items that are on sale. A variable-weight index will better reflect the effective price level in the category.

A cost of using this particular price index is that our index can suffer from “composition bias” in that the index can change even though none of the prices of the items that make up the index change (see Jack E. Triplet, 2003, for further discussion of the merits of various index schemes for high-frequency data). Our view is that composition bias is not a significant problem in our data given the similar average price of standardized units of the items in the aggregates. In order to insure that our results are robust to these issues, we recomputed the results in Tables 3, 4, and 6 using fixed-weight price indices, which are immune to these composition bias problems. The qualitative results remain the same. The standard errors increase somewhat due to lower variation in the index. However, the majority of the category-level price declines documented in Table 3 remain statistically significant using fixed-weight price indices.

Having selected categories with different patterns of seasonal demand and having constructed items and category price and quantity indices, we now turn to an inspection of the seasonal pattern of prices.

### III. How Do Prices Move Over the Demand Cycle?

We consider prices at two levels of aggregation: (1) the item level, and (2) the overall category level. In both cases, these prices are formed by combining store-level prices to form chain-wide price indices. Given that DFF uses essentially three pricing zones for the entire Chicago area, this aggregation procedure obscures very little across-store heterogeneity in prices. For more information about DFF's pricing zones, see Stephen J. Hoch et al. (1995).

#### A. “Item”-Level Analysis

In Table 2, we present results from regressions of the log of the price of each item aggregate on a linear and quadratic trend, the temperature measures, and the holiday dummies. Due to the large number of aggregates, we present results only for the temperature/holiday coefficients of interest (coefficients for all variables will be presented for the category-level analysis below). To summarize the evidence, we report a pair of additional statistics. One indicator is the mean of the coefficients within a category for each holiday/seasonal shock. A second measure of the average coefficient is shown in the rightmost column of Table 2. These estimates were calculated by estimating the price equation for each item aggregate in the category using a restricted Seemingly Unrelated Regression (SUR). Each item aggregate was allowed to have its own coefficient for trend terms and the weather and holiday variables that were expected to be unimportant for that category. The coefficient for the predicted demand spikes were constrained to be the same for all items in the category. These restricted coefficients are shown in the rightmost column of Table 2.

Table 2 shows that, in general, prices tend to be lower rather than higher during the periods of peak demand for an item. Indeed, 13 of the 14 average coefficients corresponding to hypothesized peak demand periods are negative, with the exception of the average coefficient of cold weather for cooking soups (and one might well anticipate that demand for cooking soups would not be as temperature-sensitive as for eating soups). The restricted regression coefficients show the same pattern, although by this metric July 4th also shows no price change for beer.

The pronounced tendency for retail prices to be lower at these demand peaks is unexpected given the standard textbook case of price equal to marginal cost and constant (or decreasing) returns to scale unless there are seasonal patterns in the marginal cost which exactly match the demand patterns we have identified. This seems particularly unlikely for several reasons.

First, the final two panels of Table 2 are highly suggestive that this hypothesis is false. Presumably, the marginal costs of producing and distributing cooking soups and eating soups

TABLE 2—ESTIMATED PRICE EFFECTS AT PEAK DEMAND PERIODS  
FOR INDIVIDUAL ITEM AGGREGATES

| Variable                | Number of negative<br>coefficients/total<br>coefficients estimated | Average<br>estimated<br>coefficient | Restricted<br>SUR<br>(standard error) |
|-------------------------|--------------------------------------------------------------------|-------------------------------------|---------------------------------------|
| Panel A: Beer           |                                                                    |                                     |                                       |
| Hot                     | 7/8                                                                | −0.14                               | −0.17<br>(0.03)                       |
| Memorial Day            | 6/8                                                                | −2.93                               | −0.98<br>(1.10)                       |
| July 4th                | 6/8                                                                | −0.83                               | 0.01<br>(1.10)                        |
| Labor Day               | 4/8                                                                | −0.26                               | −0.56<br>(1.10)                       |
| Christmas               | 8/8                                                                | −4.56                               | −3.80<br>(1.00)                       |
| Panel B: Oatmeal        |                                                                    |                                     |                                       |
| Cold                    | 4/6                                                                | −0.09                               | −0.006<br>(0.02)                      |
| Panel C: Tuna           |                                                                    |                                     |                                       |
| Lent                    | 7/7                                                                | −4.93                               | −1.9<br>(0.42)                        |
| Panel D: Snack Crackers |                                                                    |                                     |                                       |
| Christmas               | 6/9                                                                | −9.02                               | −1.700<br>(0.65)                      |
| Thanksgiving            | 6/9                                                                | −5.93                               | −1.400<br>(0.79)                      |
| Panel E: Cheese         |                                                                    |                                     |                                       |
| Christmas               | 8/8                                                                | −5.51                               | −2.9<br>(0.46)                        |
| Thanksgiving            | 6/8                                                                | −2.30                               | −1.2<br>(0.77)                        |
| Panel F: Eating Soups   |                                                                    |                                     |                                       |
| Cold                    | 6/7                                                                | −0.032                              | −0.052<br>(0.02)                      |
| Thanksgiving            | 1/7                                                                | 2.06                                | 0.29<br>(0.62)                        |
| Panel G: Cooking Soups  |                                                                    |                                     |                                       |
| Cold                    | 3/5                                                                | 0.00                                | −0.039<br>(0.02)                      |
| Thanksgiving            | 5/5                                                                | −3.51                               | −1.24<br>(9.8)                        |

*Notes:* Independent variables are shown in each panel for the predicted seasonal demand peaks for that category. Each panel reports on regressions of price on holiday and seasonal dummies for each item aggregate in the category. The “average estimated coefficient” shows the mean coefficient obtained across the regressions for each item aggregate. Restricted SUR coefficients represent the coefficient obtained from a seemingly unrelated regression in which the coefficients for each item aggregate in the category are constrained to be the same. Coefficients for the unreported independent variables were allowed to vary for each item.

are *extremely* highly correlated. Nonetheless, the pricing patterns for the two types of soups are very different. All five of the cooking soups experience price declines at Thanksgiving, while only one of the seven eating soups declines in price at Thanksgiving. The cooking soup prices show little response to cold weather, while six of the seven eating soup prices decline during the cold weather.

A similar argument can be made for the two types of crackers. Again, we expect the marginal cost of producing and distributing regular and snack crackers to be extremely highly correlated. However, we find that, in sharp contrast to the behavior of snack cracker prices, all six of the regular cracker aggregates show price increases at Christmas. Furthermore, two of the six regular cracker aggregates have price increases at Christmas that are statistically significant at the 5-percent level. Thus, we have two examples of products that should have very similar production functions but different demand patterns. In both cases, prices fall for the seasonal good during the peak demand period.

Second, MacDonald (2000) has checked some of the input costs for baking and dairy products and found that these do not exhibit countercyclical patterns. In fact, during the Thanksgiving–Christmas holiday period when demand for baking products is highest, the costs are actually higher than normal.

One important observation about the findings in Table 2 is that both the individual coefficients and the restricted SUR coefficients are generally quite small and often indistinguishable from zero. Furthermore, even when the average coefficient for a category is negative, the coefficients for most categories/holidays are not uniformly negative. However, as we now explain, the methodology of Table 2 likely understates the importance of seasonal price declines to both retailers and consumers.

### B. “Category”-Level Analysis

Suppose (contrary to fact) that the items within a category were perfect substitutes and that the retailer offered a special seasonal discount on just one of the items in the category. In this case, all consumers would only purchase the discounted item. Under the strong assumption of perfect substitutability, holding a sale on

one item is identical to holding a sale on all items. Examining average price responses to a seasonal demand shock for individual aggregates will understate the importance of the price reductions. We, therefore, now consider the category price indices constructed with variable weights as outlined in Section II, subsection E.

Regression results with variable-weight price indices for these constructed categories are contained in Table 3. An inspection of ordinary least-squares (OLS) regressions using the aggregated data shows clear evidence of nonnormality of the error terms. This is especially true when we use the noisy margin data described below. Thus, for all regressions in which we undertake aggregation, we perform the estimations using an iterative generalized least-squares (GLS) procedure. The GLS procedure will attain about 95 percent of the efficiency of OLS when errors are distributed normally and will outperform OLS when the error distribution is heavy-tailed, as appears to be the case for our data.<sup>1</sup> In general, the unreported OLS results show *larger* holiday and seasonal price declines than the robust regression results that we present here.

In the category-level, variable-weight price regressions, all 14 of the coefficients corresponding to hypothesized demand spikes are negative. The negative coefficients for many, including beer during the hot weather, beer at July 4th and Labor Day, tuna at Lent, snack crackers at Christmas and Thanksgiving, cheese at Christmas and Thanksgiving, eating soup in the cold weather and cooking soup at Thanksgiving, are statistically different from zero at the 5-percent level. The magnitudes of the coefficients for most of the holiday variables are substantial. Both tuna at Lent and snack crackers and cheese at Christmas have estimated price declines of at least 10 percent.

The coefficients for the temperature variables remain small. The coefficient for “HOT” for beer implies that, from April 25th when the temperature should be approximately 49

<sup>1</sup> Specifically, we calculate starting values and then perform Huber iterations (Peter J. Huber, 1964) until convergence followed by biweight iterations (Albert E. Beaton and John W. Tukey, 1974) until convergence. A description of this procedure can be found in Lawrence C. Hamilton (1991).

TABLE 3—SEASONAL RETAIL PRICE CHANGES: CATEGORY AGGREGATES

| Panel A: Seasonal Categories    |                               |                               |                               |                                |                               |                                |                                |
|---------------------------------|-------------------------------|-------------------------------|-------------------------------|--------------------------------|-------------------------------|--------------------------------|--------------------------------|
| Variable                        | Beer                          | Eating soup                   | Oatmeal                       | Cheese                         | Cooking soup                  | Snack crackers                 | Tuna                           |
| Linear trend                    | -0.12<br>(0.04)               | 0.28<br>(0.01)                | 0.14<br>(0.01)                | 0.020<br>(0.010)               | 0.30<br>(0.01)                | 0.09<br>(0.01)                 | -0.03<br>(0.02)                |
| Quadratic trend                 | 0.0004<br>(0.0001)            | -0.0005<br>(0.00003)          | -0.0002<br>(0.0003)           | -0.0005<br>(0.00003)           | -0.0004<br>(0.00002)          | -0.0001<br>(0.00003)           | 0.0002<br>(0.00004)            |
| Cold                            | -0.07<br>(0.06)               | <b>-0.13</b><br><b>(0.05)</b> | <b>-0.04</b><br><b>(0.03)</b> | 0.04<br>(0.04)                 | -0.04<br>(0.03)               | -0.03<br>(0.04)                | -0.11<br>(0.07)                |
| Hot                             | <b>-0.19</b><br><b>(0.06)</b> | -0.02<br>(0.05)               | -0.15<br>(0.03)               | -0.05<br>(0.05)                | 0.04<br>(0.03)                | 0.03<br>(0.05)                 | -0.08<br>(0.07)                |
| Lent                            |                               |                               |                               |                                |                               |                                | <b>-12.95</b><br><b>(1.82)</b> |
| Easter                          | 1.84<br>(2.07)                | -0.255<br>(1.76)              | -0.90<br>(1.13)               | -11.82<br>(1.57)               | -4.18<br>(0.98)               | -2.72<br>(1.56)                | -0.97<br>(2.54)                |
| Memorial Day                    | <b>-2.78</b><br><b>(2.01)</b> | 2.63<br>(1.83)                | 0.27<br>(1.19)                | -5.03<br>(1.63)                | 0.87<br>(1.02)                | 1.92<br>(1.62)                 | 1.51<br>(2.57)                 |
| July 4th                        | <b>-5.09</b><br><b>(1.90)</b> | 2.64<br>(1.95)                | -0.88<br>(1.16)               | -3.08<br>(1.72)                | 0.16<br>(1.08)                | -3.12<br>(1.71)                | 2.05<br>(2.71)                 |
| Labor Day                       | <b>-3.85</b><br><b>(1.85)</b> | 2.31<br>(1.90)                | 2.35<br>(1.13)                | -2.69<br>(1.68)                | 1.92<br>(1.06)                | -6.60<br>(1.67)                | 2.20<br>(2.65)                 |
| Thanksgiving                    | -1.04<br>(2.15)               | 5.65<br>(1.78)                | 1.30<br>(1.15)                | <b>-8.27</b><br><b>(1.64)</b>  | <b>-3.60</b><br><b>(0.99)</b> | <b>-6.12</b><br><b>(1.68)</b>  | 5.18<br>(2.35)                 |
| Post-Thanksgiving               | -3.23<br>(2.80)               | 5.17<br>(2.39)                | 0.17<br>(1.52)                | -5.09<br>(2.13)                | 2.20<br>(1.33)                | -7.92<br>(2.25)                | 5.07<br>(3.13)                 |
| Christmas                       | <b>-2.50</b><br><b>(1.74)</b> | 7.28<br>(1.48)                | -1.50<br>(0.95)               | <b>-10.25</b><br><b>(1.32)</b> | <b>-0.26</b><br><b>(0.83)</b> | <b>-12.05</b><br><b>(1.38)</b> | 5.95<br>(1.99)                 |
| Constant                        | -306.73<br>(4.03)             | -301.82<br>(1.23)             | -209.42<br>(1.73)             | 108.8<br>(10.89)               | -315.83<br>(0.68)             | -175.51<br>(1.08)              | -190.6<br>(1.65)               |
| Number of weeks                 | 219                           | 387                           | 304                           | 390                            | 387                           | 385                            | 339                            |
| Panel B: Nonseasonal Categories |                               |                               |                               |                                |                               |                                |                                |
| Variable                        | Analgesics                    |                               | Cookies                       |                                | Crackers                      |                                | Dish detergent                 |
| Linear trend                    | 0.08<br>(0.01)                |                               | 0.12<br>(0.022)               |                                | 0.15<br>(0.01)                |                                | -0.04<br>(0.01)                |
| Quadratic trend                 | -0.0001<br>(0.00002)          |                               | -0.0001<br>(0.0001)           |                                | -0.0002<br>(0.00002)          |                                | 0.0001<br>(0.00003)            |
| Cold                            | 0.2<br>(0.03)                 |                               | -0.07<br>(0.09)               |                                | -0.01<br>(0.04)               |                                | -0.06<br>(0.05)                |
| Hot                             | 0.11<br>(0.03)                |                               | -0.29<br>(0.09)               |                                | 0.06<br>(0.04)                |                                | -0.09<br>(0.05)                |
| Easter                          | 0.87<br>(1.07)                |                               | -5.04<br>(3.24)               |                                | 3.45<br>(1.41)                |                                | -1.14<br>(1.62)                |
| Memorial Day                    | -0.19<br>(1.11)               |                               | 2.91<br>(3.35)                |                                | 1.48<br>(1.47)                |                                | 0.88<br>(1.68)                 |
| July 4th                        | -0.28<br>(1.17)               |                               | 6.18<br>(3.54)                |                                | 2.54<br>(1.55)                |                                | -0.99<br>(1.78)                |
| Labor Day                       | -1.81<br>(1.14)               |                               | 5.41<br>(3.46)                |                                | 2.54<br>(1.51)                |                                | 1.01<br>(1.73)                 |
| Thanksgiving                    | 0.84<br>(1.08)                |                               | 1.00<br>(3.49)                |                                | -1.19<br>(1.52)               |                                | -0.99<br>(1.63)                |
| Post-Thanksgiving               | 1.51<br>(1.44)                |                               | 2.81<br>(4.66)                |                                | 1.06<br>(2.04)                |                                | 0.94<br>(2.19)                 |
| Christmas                       | 2.05<br>(0.90)                |                               | 3.48<br>(2.76)                |                                | 3.42<br>(1.25)                |                                | 0.66<br>(1.36)                 |
| Constant                        | -255.93<br>(0.74)             |                               | -184.04<br>(2.25)             |                                | -225.41<br>(0.98)             |                                | -272.89<br>(1.12)              |
| Number of weeks                 | 391                           |                               | 387                           |                                | 385                           |                                | 391                            |

Notes: The dependent variable in each column is the log of the variable-weight price index for each category. Units in the table are percentage points. Bold type indicates period of expected demand peaks. Standard errors are in parentheses.

degrees until July 1st, when the temperature should be approximately 74.5 degrees, the price of beer is predicted to fall by 4.8 percent due to the temperature change. Since the hottest week is also, in fact, the week of the July 4th holiday, the total price predicted price difference between April 25th and July 1st is 9.9 percent. For eating soup, the difference between the predicted April 25th price and the price on January 25th (the coldest week of the year, with a predicted temperature of 20 degrees) is 3.8 percent. Estimated price declines for cooking soup and oatmeal are smaller still, with price declines of 1.2 percent between April 25th and the coldest week.

While at this point we have investigated only prices, not margins, we are still in a position to make some judgments about the competing theories. We have found price declines for goods at all demand spikes *for that good*. When applied to retail competition, both the R-S and W-B models predict a reduction in overall retail margin during aggregate demand shocks such as Christmas. Evidence consistent with this would be a fall in retail prices during aggregate demand shocks. Table 3 strongly suggests that price declines are far from being pervasive for the Christmas demand shock. For example, six of the seven price changes are positive for Christmas, four of these are significant at the 5-percent level.

In the face of idiosyncratic demand shocks such as warm weather for beer and Lent for canned tuna, the R-S and W-B models predict no response in overall retail margins. Our findings of price cuts for beer in warm weather and for tuna on Lent are difficult to reconcile with the retail version of the R-S and W-B models.

Should we then conclude that the R-S or W-B explanations do not apply to retailer competition for our data? In fact the R-S and W-B models only imply that overall margins should decline. In a multiproduct context, this could be achieved in an infinite number of ways, through different combinations of increases and declines. For example, the Lent canned tuna declines could be exactly matched by appropriate increases elsewhere, even without any change in wholesale prices. Without observing all prices in the store, both the R-S and W-B theories can never be refuted with 100-percent confidence. Unfortunately, we only observe

prices for items in categories that correspond to roughly 30 percent of the store volume, so we can never rule out compensating changes in prices for the goods we do not observe.

However, we did generate an overall price index for all 29 categories for which we have data. Regression results from correlating this overall price index with our set of time trend and holiday dummy variables do not show an overall decrease in prices at Christmas or Thanksgiving, the two highest sales periods. If anything, we observe a slight increase in prices. We construct an overall price index with both variable and fixed weights in order to make sure that our results are robust to composition bias considerations. With either variable- or fixed-weight indices, the results are similar and do not show any drop in prices at Christmas or Thanksgiving.

The pattern of coefficients in Table 3 are also suggestive that the price patterns are not due to overall increasing returns to scale on the part of the retailer. The efficiency gains at times of high shopping could explain the price drops for the goods whose demand peaks occur at times with high overall purchases. But this mechanism cannot explain why the idiosyncratic demand surges are accompanied by price declines.

The results in this section are consistent with several theoretical hypotheses. First, if the price declines largely reflect declines in retail margins, the results are consistent with the loss-leader models. Retailers are choosing to advertise discounts on goods that are popular in any given week. On the other hand, if the price declines appear to be largely the result of seasonal changes in manufacturer margins, this could be evidence for R-S or W-B behavior on the part of manufacturers rather than retailers.

To further distinguish between competing theories, we need to separately examine the behavior of retail margins and wholesale prices over the seasonal and holiday cycle.

#### IV. The Movement of Retail Margins Over the Demand Cycle

In principle, the price movements observed in Tables 2 and 3 could be the result of either manufacturer price changes or retailer price changes. To explore this, we use data obtained from DFF to calculate an estimate of the retail

margin. The margin that we calculate, the price minus the wholesale cost, divided by price is presumably an overestimate of the true margin, since it includes no retailer marginal costs other than the wholesale price. Results for regressions using retail margins are found in Table 4. The methodology used here is identical to that in Table 3. That is, we use our category-level variable-weight price indices to calculate retail margins. This seems most relevant given our finding that category-level prices move more than item-level prices (and because the retailer's profits are driven by the total category sales.)

Consider first the changes in retail margins at holidays for holiday-seasonal goods. All of the theories that we highlight predict falling retail margins at those holidays that correspond to aggregate store-level demand spikes. Clearly, Thanksgiving and Christmas can be defined as store-level aggregate demand spikes. Arguably, July 4th, Memorial Day, Labor Day, and Easter are also store-level aggregate demand spikes, albeit smaller ones.

The fall in retail margins during these holidays for these holiday-sensitive goods is clear. Negative price responses, significantly different from zero at the 5-percent level, are found for cheese and snack crackers at Thanksgiving and Christmas, and beer at Memorial Day, July 4th, Labor Day, and Christmas (New Year's). The only good not demonstrating this pattern is cooking soup. Cooking soup has a tiny and statistically insignificant retail margin decline at Thanksgiving, its primary demand shift. Margins on cooking soup actually increase slightly at Christmas, the secondary demand shift.

More interesting from the perspective of separating out the theories are the results for retail tuna margins at Lent. Retail margins on tuna decline 5 percentage points at Lent. This decrease is statistically significant at the 1-percent confidence level. Recall that Lent is not a positive aggregate demand shock for the supermarket. The fact that tuna margins decline and that the decline is on the same order of magnitude as the declines observed for the other holiday goods strongly suggests that the aggregate demand-driven models of imperfect competition among retailers (R-S and W-B) do not appear to be at work here.

The retail margin behavior for the cold/hot seasonal products provides some further, albeit

weak, support for this view. Beer, oatmeal, and eating soup all show margin declines during their peak demand seasons. These declines are statistically significant at the 5-percent level for oatmeal and for soup. However, the magnitudes are tiny. The predicted decline in margin is 2.0 percentage points from the median temperature week to the coldest week for soup and 1.2 percentage points for oatmeal. The predicted decline in margin for beer is less than 1 percent from the median temperature week to the hottest week.

The results for the nonseasonal goods cast further doubt on the R-S and W-B models for the retailers. These models would suggest that retail margins during aggregate demand shocks such as Thanksgiving or Christmas should be lower on average across all categories. This is impossible to judge given that we do not have data on all categories. But the data that we do have do not suggest that this is happening. Among the goods where we expect no demand shifts at Thanksgiving and Christmas, none show a significant decrease in price. To the extent there is a pattern it seems that more category margins rise than fall.

Altogether, the evidence on retail margins is most consistent with loss-leader models. These models produce a rationale for why retailers would accept lower margins on any good experiencing a demand surge, whether or not that demand surge corresponds to an aggregate demand peak. Furthermore, the Lal and Matutes (1994) variant of the model suggests that prices are low on advertised items but the shopper's reservation price is charged for the unadvertised items. Thus, their model is easy to reconcile with a finding that the average margin on all products in the store could rise at the periods of peak demand.

One further possible explanation for the measured decline in retailer margins at both aggregate and idiosyncratic demand peaks is that true marginal cost is falling due to reduction in inventory costs. This is a variant of the increasing returns hypothesis described in Section I, subsection D. If the items in our analysis turn over more frequently at the demand peaks then the inventory component of marginal cost will decrease. Of course, it is not obvious that items turn over more rapidly during a demand spike, as retailers may adjust shelf space allocations

TABLE 4—SEASONAL CHANGES IN RETAIL MARGINS

| Panel A: Seasonal Categories    |                               |                               |                               |                               |                               |                               |                               |
|---------------------------------|-------------------------------|-------------------------------|-------------------------------|-------------------------------|-------------------------------|-------------------------------|-------------------------------|
| Variable                        | Beer                          | Eating soup                   | Oatmeal                       | Cheese                        | Cooking soup                  | Snack crackers                | Tuna                          |
| Linear trend                    | −0.21<br>(0.03)               | 0.04<br>(0.01)                | 0.04<br>(0.01)                | −0.009<br>(0.010)             | 0.04<br>(0.01)                | 0.01<br>(0.01)                | −0.01<br>(0.01)               |
| Quadratic trend                 | 0.0004<br>(0.00007)           | −0.00009<br>(0.00002)         | −0.00008<br>(0.00002)         | 0.00006<br>(0.00002)          | −0.00003<br>(0.00001)         | 0.00002<br>(0.00002)          | 0.00006<br>(0.00002)          |
| Cold                            | −0.01<br>(0.04)               | <b>−0.07</b><br><b>(0.03)</b> | <b>−0.04</b><br><b>(0.02)</b> | 0.004<br>(0.03)               | 0.02<br>(0.02)                | 0.00<br>(0.03)                | −0.02<br>(0.04)               |
| Hot                             | <b>−0.03</b><br><b>(0.04)</b> | −0.10<br>(0.03)               | −0.02<br>(0.02)               | −0.08<br>(0.03)               | −0.05<br>(0.02)               | −0.03<br>(0.03)               | −0.07<br>(0.04)               |
| Lent                            |                               |                               |                               |                               |                               |                               | <b>−5.03</b><br><b>(1.06)</b> |
| Easter                          | 0.88<br>(1.48)                | 0.34<br>(1.07)                | 0.66<br>(0.65)                | −2.57<br>(1.17)               | −1.49<br>(0.84)               | −0.39<br>(1.20)               | −1.82<br>(1.47)               |
| Memorial Day                    | <b>−4.36</b><br><b>(1.44)</b> | 1.35<br>(1.11)                | 1.17<br>(0.69)                | −0.54<br>(1.22)               | 0.42<br>(0.87)                | 1.59<br>(1.24)                | −1.16<br>(1.49)               |
| July 4th                        | <b>−4.08</b><br><b>(1.36)</b> | 2.18<br>(1.18)                | 0.27<br>(0.67)                | −0.33<br>(1.29)               | 0.81<br>(0.92)                | −1.01<br>(1.31)               | 1.82<br>(1.57)                |
| Labor Day                       | <b>−2.61</b><br><b>(1.33)</b> | 1.42<br>(1.15)                | 0.19<br>(0.65)                | 0.27<br>(1.25)                | 0.05<br>(0.90)                | −4.61<br>(1.28)               | −1.50<br>(1.53)               |
| Thanksgiving                    | −1.31<br>(1.54)               | 1.54<br>(1.08)                | 0.01<br>(0.66)                | <b>−5.18</b><br><b>(1.18)</b> | <b>−0.68</b><br><b>(0.84)</b> | <b>−5.04</b><br><b>(1.29)</b> | 2.27<br>(1.36)                |
| Post-Thanksgiving               | −3.12<br>(2.00)               | 0.87<br>(1.44)                | −1.25<br>(0.88)               | −4.15<br>(1.59)               | 0.13<br>(1.13)                | −4.54<br>(1.72)               | 0.63<br>(1.81)                |
| Christmas                       | <b>−2.66</b><br><b>(1.25)</b> | 2.34<br>(0.90)                | −0.42<br>(0.55)               | <b>−3.23</b><br><b>(0.98)</b> | <b>0.51</b><br><b>(0.70)</b>  | <b>−8.47</b><br><b>(1.06)</b> | 1.00<br>(1.15)                |
| Constant                        | 28.57<br>(2.88)               | 18.42<br>(0.74)               | 17.99<br>(1.00)               | 34.38<br>(0.81)               | 14.21<br>(0.58)               | 22.84<br>(0.83)               | 25.64<br>(0.96)               |
| Number of weeks                 | 219                           | 387                           | 304                           | 391                           | 387                           | 385                           | 339                           |
| Panel B: Nonseasonal Categories |                               |                               |                               |                               |                               |                               |                               |
| Variable                        | Analgesics                    |                               | Cookies                       |                               | Crackers                      |                               | Dish detergent                |
| Linear trend                    | 0.01<br>(0.00)                |                               | 0.01<br>(0.01)                |                               | 0.02<br>(0.01)                |                               | −0.11<br>(0.01)               |
| Quadratic trend                 | 0.00002<br>(0.00001)          |                               | 0.00001<br>(0.00002)          |                               | 0.00000<br>(0.00002)          |                               | 0.00028<br>(0.00002)          |
| Cold                            | −0.02<br>(0.02)               |                               | 0.1<br>(0.03)                 |                               | −0.01<br>(0.03)               |                               | 0.02<br>(0.04)                |
| Hot                             | −0.01<br>(0.02)               |                               | −0.08<br>(0.03)               |                               | −0.03<br>(0.03)               |                               | −0.07<br>(0.04)               |
| Easter                          | 0.92<br>(0.73)                |                               | −2.71<br>(1.11)               |                               | 0.93<br>(1.10)                |                               | 1.46<br>(1.39)                |
| Memorial Day                    | 0.08<br>(0.75)                |                               | 1.84<br>(1.15)                |                               | 0.16<br>(1.14)                |                               | 1.10<br>(1.44)                |
| July 4th                        | 0.88<br>(0.80)                |                               | 1.61<br>(1.21)                |                               | −0.31<br>(1.21)               |                               | 0.60<br>(1.52)                |
| Labor Day                       | −0.87<br>(0.78)               |                               | 1.29<br>(1.18)                |                               | 0.58<br>(1.18)                |                               | 2.13<br>(1.49)                |
| Thanksgiving                    | −0.51<br>(0.73)               |                               | −1.11<br>(1.19)               |                               | 0.73<br>(1.19)                |                               | 0.53<br>(1.40)                |
| Post-Thanksgiving               | −1.57<br>(0.98)               |                               | −0.53<br>(1.60)               |                               | −0.55<br>(1.59)               |                               | 1.99<br>(1.88)                |
| Christmas                       | 0.50<br>(0.61)                |                               | 1.04<br>(0.95)                |                               | 0.40<br>(0.98)                |                               | 1.16<br>(1.17)                |
| Constant                        | 25.25<br>(0.50)               |                               | 24.14<br>(0.77)               |                               | 27.05<br>(0.77)               |                               | 27.09<br>(0.96)               |
| Number of weeks                 | 391                           |                               | 387                           |                               | 385                           |                               | 391                           |

Notes: The dependent variable in each column is the log of the variable-weight retail margin for each category. Units in the table are percentage points. Bold type indicates periods of expected demand peaks. Standard errors are in parentheses.

when the demand for a particular item spikes (such as by allocating “aisle caps” to an item in high demand).

However, it is instructive to consider how large these reductions in inventory costs can plausibly be. If the supermarket’s overall capital investment decision is optimal, the cost of inventorying a product is the lost interest on the capital invested in the product plus the rental cost of the space that the item takes up.<sup>2</sup> The second of these is negligible for the products that we are discussing. How high can the interest saving be of turning over an item more quickly? Suppose that the typical item is held in inventory for one month and that a demand spike doubles sales, leading the item to be held in inventory for only two weeks. Both of these assumptions are biased to make the cost savings look large, as the items in our study are generally “turned” more than 12 times per year, and a doubling of demand in a month is much larger than the spikes that we observe for any of our products. At an annual simple interest rate of 12 percent, the interest cost of carrying inventory is 1 percent per month. The cost savings of turning over the inventory twice as fast, then, amounts to a savings of about 0.5 percent over the one-month demand spike. This is small relative to the reductions in margins that we find at holiday spikes for our goods.

The results in this section are predicated on the accuracy of our retail margin data. Our results assume that the wholesale prices observed represent a true measure of acquisition cost. If manufacturer employed nonlinear pricing schemes or side payments, then our measures of acquisition cost might deviate from true cost. While we cannot rule out these practices altogether, there is good reason to believe that they are quite limited. Manufacturers are very sensitive to various Robinson-Patman concerns and typically post wholesale prices on a market-by-market basis rather than retailer-by-retailer. For example, Nabisco will post a wholesale cost per case for Oreo cookies for the Chicago mar-

ket. Any retailer can order at this price. Retailers are extremely good at arbitraging wholesale price differences that do appear across markets (by using various transshipment schemes). These enforcement problems limit the use of nonlinear pricing.

## V. The Behavior of Wholesale Prices Over the Demand Cycle

The acceptance or rejection of any particular model of retailer behavior does not narrow down the set of possible theories governing manufacturer behavior. We know that the observed price declines for goods at their seasonal demand peaks are at least partially the result of declining retail margins for those goods. However, these price declines could also be partially due to changes in manufacturer margins or costs over the seasonal cycle.

In Table 5 we examine changes in wholesale prices over the seasonal cycle. Changes in wholesale prices are generally negative at demand peaks for a good; 10 of the 14 point estimates are negative for the peak periods. But only four of the estimates (beer in the hot weather, snack crackers at Christmas, cooking soup at Thanksgiving, and tuna at Lent) are statistically different from 0 at the 5-percent level. Moreover, most of the estimates are small, not only in absolute terms, but also in relation to the retail margin changes. On balance, we read the evidence as saying that manufacturer behavior plays a more limited role in the countercyclical of prices than retailer behavior.

Because we lack data on manufacturer costs, we cannot definitively answer why manufacturer prices show a tendency to fall at seasonal demand peaks for some of our products. These price drops could have many causes—increasing returns to scale in production, tacit collusion among manufacturers, or increased within-category price sensitivity at seasonal demand peaks.

Although all of these explanations are possible, we are doubtful of tacit collusion among manufacturers as an explanation for the observed seasonality of wholesale prices. The list of manufacturers participating in the cookies, crackers, and snack crackers categories are virtually identical. Yet, the demand cycles for

<sup>2</sup> That is, during a period of “normal” demand, we would expect that the shadow cost of the space is set equal to the actual cost of space in the market. During an aggregate demand peak, of course, space is not adjustable and the shadow cost of shelf space may be higher than the market rental rate.

TABLE 5—SEASONAL CHANGES IN WHOLESALE PRICES

| Panel A: Seasonal Categories    |                                 |                                |                                 |                                 |                                 |                                 |                                 |
|---------------------------------|---------------------------------|--------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|
| Variable                        | Beer                            | Eating soup                    | Oatmeal                         | Cheese                          | Cooking soup                    | Snack crackers                  | Tuna                            |
| Linear trend                    | 0.08<br>(0.02)                  | 0.23<br>(0.01)                 | 0.09<br>(0.02)                  | 0.022<br>(0.012)                | 0.26<br>(0.01)                  | 0.85<br>(0.01)                  | -0.03<br>(0.01)                 |
| Quadratic trend                 | -0.00003<br>(0.00006)           | -0.00032<br>(0.00001)          | -0.00012<br>(0.00003)           | -0.00001<br>(0.00003)           | -0.00042<br>(0.00001)           | -0.00014<br>(0.00002)           | 0.00015<br>(0.00004)            |
| Cold                            | -0.02<br>(0.03)                 | <b>0.01</b><br>( <b>0.03</b> ) | <b>-0.01</b><br>( <b>0.04</b> ) | 0.011<br>(0.05)                 | -0.05<br>(0.02)                 | -0.04<br>(0.03)                 | -0.05<br>(0.06)                 |
| Hot                             | <b>-0.16</b><br>( <b>0.03</b> ) | 0.11<br>(0.03)                 | -0.14<br>(0.04)                 | 0.06<br>(0.05)                  | 0.12<br>(0.02)                  | 0.06<br>(0.03)                  | 0.00<br>(0.06)                  |
| Lent                            |                                 |                                |                                 |                                 |                                 |                                 | <b>-7.26</b><br>( <b>1.59</b> ) |
| Easter                          | 0.80<br>(1.17)                  | -0.09<br>(0.91)                | -1.77<br>(1.25)                 | -4.4<br>(1.81)                  | -1.88<br>(0.79)                 | -0.64<br>(1.12)                 | 1.70<br>(2.18)                  |
| Memorial Day                    | <b>1.93</b><br>( <b>1.13</b> )  | 0.92<br>(0.95)                 | -1.48<br>(1.32)                 | -3.91<br>(1.88)                 | 0.41<br>(0.82)                  | 0.31<br>(1.17)                  | 3.47<br>(2.20)                  |
| July 4th                        | <b>-0.45</b><br>( <b>1.07</b> ) | 0.23<br>(1.0)                  | -1.33<br>(1.28)                 | -3.68<br>(1.98)                 | -0.96<br>(0.87)                 | -2.69<br>(1.23)                 | 0.43<br>(2.33)                  |
| Labor Day                       | <b>-0.82</b><br>( <b>1.04</b> ) | -0.39<br>(0.98)                | 2.6<br>(1.24)                   | -2.51<br>(1.94)                 | 0.75<br>(0.85)                  | 1.75<br>(1.20)                  | 4.0<br>(2.27)                   |
| Thanksgiving                    | -0.12<br>(1.21)                 | 2.83<br>(0.92)                 | 2.51<br>(1.68)                  | <b>0.73</b><br>( <b>1.82</b> )  | <b>-2.94</b><br>( <b>0.80</b> ) | <b>-0.11</b><br>( <b>1.21</b> ) | 1.63<br>(2.01)                  |
| Post-Thanksgiving               | -0.17<br>(1.58)                 | 3.72<br>(1.23)                 | 2.51<br>(1.68)                  | 1.91<br>(2.45)                  | -3.0<br>(1.07)                  | -1.45<br>(1.62)                 | 0.85<br>(2.68)                  |
| Christmas                       | <b>0.22</b><br>( <b>0.98</b> )  | 3.11<br>(0.77)                 | -2.12<br>(1.05)                 | <b>-2.90</b><br>( <b>1.52</b> ) | <b>-0.32</b><br>( <b>0.67</b> ) | <b>-2.74</b><br>( <b>1.00</b> ) | 3.13<br>(1.71)                  |
| Constant                        | -334.53<br>(2.27)               | -322.03<br>(0.63)              | -229.53<br>(1.91)               | 66.53<br>(1.25)                 | -331.83<br>(0.55)               | -201.56<br>(0.78)               | -219.64<br>(1.42)               |
| Number of weeks                 | 219                             | 387                            | 304                             | 391                             | 387                             | 385                             | 338                             |
| Panel B: Nonseasonal Categories |                                 |                                |                                 |                                 |                                 |                                 |                                 |
| Variable                        | Analgesics                      |                                | Cookies                         |                                 | Crackers                        |                                 | Dish detergent                  |
| Linear trend                    | 0.08<br>(0.01)                  |                                | 0.09<br>(0.01)                  |                                 | 0.11<br>(0.01)                  |                                 | 0.11<br>(0.01)                  |
| Quadratic trend                 | -0.00013<br>(0.00129)           |                                | -0.00011<br>(0.00003)           |                                 | -0.00019<br>(0.00003)           |                                 | -0.00032<br>(0.00003)           |
| Cold                            | 0.02<br>(0.02)                  |                                | -0.01<br>(0.06)                 |                                 | -0.01<br>(0.05)                 |                                 | -0.04<br>(0.05)                 |
| Hot                             | 0.08<br>(0.02)                  |                                | -0.07<br>(0.06)                 |                                 | 0.14<br>(0.05)                  |                                 | 0.03<br>(0.05)                  |
| Easter                          | -0.23<br>(0.80)                 |                                | -1.20<br>(2.14)                 |                                 | 2.63<br>(1.65)                  |                                 | -0.67<br>(1.75)                 |
| Memorial Day                    | -0.62<br>(0.83)                 |                                | -0.07<br>(2.22)                 |                                 | 2.29<br>(1.71)                  |                                 | 1.15<br>(1.81)                  |
| July 4th                        | -0.59<br>(0.88)                 |                                | 1.69<br>(2.35)                  |                                 | 1.64<br>(1.81)                  |                                 | 0.26<br>(1.92)                  |
| Labor Day                       | -0.92<br>(0.86)                 |                                | -0.16<br>(2.29)                 |                                 | 2.27<br>(1.77)                  |                                 | -0.97<br>(1.87)                 |
| Thanksgiving                    | 1.92<br>(0.81)                  |                                | 1.48<br>(2.31)                  |                                 | -3.19<br>(1.78)                 |                                 | -2.11<br>(1.76)                 |
| Post-Thanksgiving               | -0.15<br>(1.08)                 |                                | 2.49<br>(3.09)                  |                                 | 2.60<br>(2.38)                  |                                 | -2.13<br>(2.37)                 |
| Christmas                       | 1.08<br>(0.67)                  |                                | 1.71<br>(1.83)                  |                                 | 4.28<br>(1.47)                  |                                 | -1.36<br>(1.47)                 |
| Constant                        | -284.63<br>(0.55)               |                                | -211.19<br>(1.49)               |                                 | -256.44<br>(1.15)               |                                 | -306.29<br>(1.21)               |
| Number of weeks                 | 391                             |                                | 387                             |                                 | 385                             |                                 | 391                             |

Notes: The dependent variable in each column is the log of the variable-weight wholesale price index for each category. Units in the table are percentage points. Bold type indicates periods of expected demand peaks. Standard errors are in parentheses.

these products are not very well synchronized. For example, the (detrended) quantities sold of cookies is *negatively* correlated with purchases of snack crackers and regular crackers, and the correlation between snack cracker and regular cracker purchases is only 0.10.

The logic of Bernheim and Whinston (1990) suggests that multimarket contact can mitigate the countercyclical margins effect identified by Rotemberg and Saloner (1986) if the demand peaks for goods are asynchronous. One would expect that colluding manufacturers who meet in several markets would face a significant temptation to cheat only when aggregate demand across those markets is high.

Yet, while wholesale prices for snack crackers decline 2.7 percent at Christmas, wholesale prices for regular crackers increase a statistically significant 4.3 percent. If the countercyclical of manufacturer prices is due to countercyclical collusion, then manufacturers must be colluding on a suboptimal product-by-product basis.

Finally, our evidence on the nature of wholesale prices differs from that presented by Philip Nelson et al. (1992), who note that wholesale prices for a national brand of coffee are higher in geographic areas in which the market share of this brand is the highest. In our seasonal context, this would imply an increase in wholesale prices during periods of peak demand. It should be noted, however, that higher market share can be achieved for many reasons, only one of which is higher demand.

## VI. Seasonal Patterns in Price Elasticity

One clear implication of the Warner and Barsky theory is that price sensitivity should vary systematically with seasonal demand peaks. Consumers appear more price sensitive due to increased search activity. Warner and Barsky suggest that this search activity occurs across stores so that in periods of peak aggregate demand consumers are willing to shop more outlets. In this case, the retailers would find it in their interest to cut margins. Alternatively, we could also interpret the search explanation as applying to search within a category at a given store. If so, this could lead manufacturers to compete with each other to have their products discounted by the retailer. This possibility

means that we could expect to see price sensitivity increasing (and manufacturer prices falling) when there is a peak in seasonal demand for a category even if that peak does not coincide with peaks in aggregate grocery demand.

While the heightened price sensitivity is central to the Warner and Barsky mechanism, neither the loss-leader nor the tacit collusion explanations require any seasonal variation in price elasticity. To the extent that time-varying price elasticities can be measured, we should be able to use this to further discriminate between the Warner and Barsky view and the other explanations.

To estimate time-varying price elasticities, we employ a simple random coefficient demand specification with store-level data. We use category-level quantity and price indices in this specification.

$$\begin{aligned}
 (1) \quad \ln q_{jt} &= \alpha + \alpha_j + \gamma' s_{jt} + \beta_p \ln p_{jt} \\
 &+ \beta_{thx} Thx \times \ln p_{jt} + \beta_{xmas} Xmas \times \ln p_{jt} \\
 &+ [\beta_{hot} Hot \times \ln p_{jt} + \beta_{cold} Cold \times \ln p_{jt} \\
 &+ \beta_{lent} Lent \times \ln p_{jt}] + \varepsilon_{jt} \\
 \alpha_j &\sim N(0, \sigma_\alpha); \varepsilon_{jt} \sim N(0, \sigma_\varepsilon)
 \end{aligned}$$

where  $j$  is the store index, the terms in brackets are added only for those categories with weather- or Lent-related expected demand peaks, and  $s_{jt}$  is a vector of time-trend variables and seasonal variables. In this specification, we are exploiting variation in seasonal prices over calendar years and over stores to estimate seasonal price elasticities. Importantly, the variation in seasonal pricing across stores is mostly occurs because “normal” prices are set at (as many as) three levels, while promotions generally involve advertising that fixes the same price for a good at all stores. Given the lower “regular” or long-run prices in the price zone designed to “fight” discount stores, the price reduction from promotions at the seasonal frequency would be less than in the other Dominick’s price zones.

Table 6 provides the results of estimation of this random coefficient model. For all categories, estimates of the change in price sensitivity

TABLE 6—TIME-VARYING PRICE SENSITIVITY

| Category                    | Price elasticity | $\log p \times Thx$             | $\log p \times Xmas$           | $\log p \times Hot$                | $\log p \times Cold$             | $\log p \times Lent$           |
|-----------------------------|------------------|---------------------------------|--------------------------------|------------------------------------|----------------------------------|--------------------------------|
| Nonseasonal Categories      |                  |                                 |                                |                                    |                                  |                                |
| Analgesics                  | -1.87<br>(0.31)  | -0.24<br>(0.096)<br>13 percent  | 0.05<br>(0.07)<br>-3 percent   |                                    |                                  |                                |
| Cookies                     | -3.6<br>(0.03)   | 0.037<br>(0.12)<br>-1 percent   | -0.074<br>(0.11)<br>2 percent  |                                    |                                  |                                |
| Dish detergent              | -3.43<br>(0.043) | -1.7<br>(0.19)<br>49 percent    | -1.1<br>(0.15)<br>32 percent   |                                    |                                  |                                |
| Crackers                    | -1.9<br>(0.037)  | 0.16<br>(0.13)<br>-8 percent    | 0.60<br>(0.10)<br>-32 percent  |                                    |                                  |                                |
| Weather-Seasonal Categories |                  |                                 |                                |                                    |                                  |                                |
| Beer                        | -5.7<br>(0.023)  | 0.067<br>(0.041)<br>-3 percent  | 0.31<br>(0.034)<br>-5 percent  | 0.0011<br>(0.00096)<br>0.4 percent |                                  |                                |
| Eating soups                | -1.98<br>(0.034) | 0.043<br>(0.060)<br>-2 percent  | -0.14<br>(0.053)<br>7 percent  |                                    | 0.019<br>(0.0014)<br>-19 percent |                                |
| Oatmeal                     | -2.93<br>(0.025) | 0.24<br>(0.075)<br>-8 percent   | 0.33<br>(0.053)<br>-11 percent |                                    | -0.0047<br>(0.0014)<br>3 percent |                                |
| Holiday-Seasonal Categories |                  |                                 |                                |                                    |                                  |                                |
| Cooking soups               | -2.18<br>(0.03)  | -0.96<br>(0.045)<br>44 percent  | -0.11<br>(0.039)<br>5 percent  |                                    |                                  |                                |
| Cheese                      | -1.2<br>(0.028)  | 1.2<br>(0.085)<br>-100 percent  | -0.66<br>(0.075)<br>55 percent |                                    |                                  |                                |
| Snack<br>crackers           | -1.6<br>(0.039)  | -1.1<br>(0.10)<br>69 percent    | -0.22<br>(0.098)<br>14 percent |                                    |                                  |                                |
| Tuna                        | -2.2<br>(0.036)  | 0.14<br>(0.090)<br>-6.4 percent | -0.11<br>(0.074)<br>5 percent  |                                    |                                  | -0.78<br>(0.057)<br>35 percent |

Notes: Each row of the table represents a separate regression, with independent variables arrayed along the columns. Price elasticity is the coefficient of  $\log p$  from equation (6). Subsequent columns represent interactions between  $\log p$  and holiday or seasonal dummy variables for the expected demand peaks for each category. Standard errors are in parentheses. The percentages shown beneath the standard errors represent the change in the baseline price coefficient associated with the listed demand peak.

at Thanksgiving and Christmas are reported. For those categories with idiosyncratic peaks in demand such as the weather-sensitive products,

we also report estimates of the change in price sensitivity for these seasonal effects. We present both the raw change in price sensitivity,

a standard error, and a percentage change in sensitivity. Note that for the Hot and Cold variables, we consider a temperature change of 20 degrees in computing the implied change in price sensitivity.

The results in Table 6 provide very little support for the basic mechanism underlying the Warner-Barsky theory. Only 5 of the 22 possible Thanksgiving/Christmas variables represent any appreciable increases in price sensitivity with several instances of significant reductions in price sensitivity. For the great majority of possibilities, there is no detectable large change in price sensitivity. It should be emphasized that our store-level data provides sufficient information to estimate these coefficients quite precisely as revealed by the small standard errors.

The results in Table 6 should be interpreted with two caveats in mind: (1) we assume that the regression errors are conditionally independent across stores and time, and (2) we assume that there is no correlation between the price variable and the regression error. The assumption of price exogeneity should be called into question in any situation in which prices are set in anticipation of some common demand shock. For example, if retailers were aware of a manufacturer coupon offer at some future date, they might adjust prices. This would make the price a function of the demand shock that would introduce a bias into the price coefficient in (6). More germane to this paper are seasonal variations in firm conduct of the sort contemplated in the Rotemberg and Saloner model. This means that the price level (or margin) would be changed again as a function of the predictable demand shock. Unless we control for this, we might also obtain biased estimates of the price elasticity.

We are able to circumvent these problems because we know when the demand shocks occur. For example, if firm conduct predictably changes at Christmas (that is collusion breaks down a bit at that time), then inclusion of a Christmas location shift and interaction term in the model will capture that effect. To be concrete, consider measuring the change in the price elasticity of demand at Christmas for cookies. Our estimates rely on two sources of variation in the data. First, an advertised promotion on cookies might represent a 10-percent discount at a Zone 1 store and a 15-percent

discount at a Zone 2 store. Second, in some years there will be no discounts (so that we can compare the sales in both zones to the years with a discount). The interaction coefficient therefore partly reflects the Christmas–non-Christmas difference between the Zone 1–Zone 2 differences. It also reflects the time variation between years in which the price promotion was held versus years in which it was not held.

Our estimates do not depend on the average changes in prices and quantities that occur at Christmas. That is, Dominick's (or the manufacturers) can systematically cut prices at Christmas and that creates no problems for the coefficients on which we focus; it is only if they can predict this particular Christmas is going to have an unusually high or low demand, and use this to inform the pricing policy that our estimates are biased.

While we cannot eliminate the possibility that year-to-year changes in the seasonal demand shocks are considered in pricing decisions, we think it unlikely that this is a serious problem. Given the average sizes of the seasonal changes in purchases and the discounts that are offered it would be difficult to make such forecasts without devoting considerable effort to the task. Moreover, we see no reason why such practices could account for the mixed nature of the results in Table 6 in which we observe both large increases and decreases in price sensitivity.

## VII. Seasonal Patterns in Advertising

Our results thus far have been very consistent with a "loss-leader" model in which the retailer advertises discounted products in an attempt to compete. But, this evidence has been indirect since it does not relate to advertising activity. A key prediction of these models is that "loss leaders" will be items in relatively high demand and that the prices of these items will be advertised. If market share can be viewed as a proxy for high demand, both Nelson et al. (1992) and Hosken and Reiffen (2001) show positive correlation between market share and the probability of being put on sale. Hosken and Reiffen (2001) also confirm this prediction by showing that high-demand items are more likely to be placed on sale.

In an effort to more directly corroborate the

loss-leader models, we explore DFF advertising. In our data set the most popular types of goods are also most prone to be advertised. For instance, among the 31 categories that comprise our data, there is a positive correlation between category-level sales and the fraction of goods sold on sale. More significantly, Table 7 confirms that advertising also varies with the seasonal cycle in the accordance with the predictions of the loss-leader models. Table 7 shows GLS regression specifications in which the left-hand-side variable is the percentage of the category revenues accounted for by items that are advertised by Dominick's. The right-hand-side variables are our usual temperature and holiday variables. The magnitudes can be interpreted as the change in the percentage of the category on advertised special during the seasonal period.

In general, seasonally peaking items are significantly more likely to be advertised. The largest increase is for the snack cracker category, where an additional 34 percent of the category is put on advertised sale. The main exceptions to the seasonality pattern are the failure of beer to be advertised more in the hot weather weeks than in the median temperature week, and the failure of soups to be advertised more in the coldest weather than in the median temperature week. (Although soups are significantly more likely to be advertised in the coldest weather than in the hottest weather.) Thus, there is some direct evidence in favor of the loss-leader models.

### VIII. Conclusions

The observation made by Warner and Barsky (1995) and MacDonald (2000), that in seasonal periods of high shopping volume, prices tend to fall, stimulates interest in classes of models with countercyclical pricing. We consider three classes of potential models: (1) the Warner-Barsky (1995) model of economies of scale in price search, (2) the Rotemberg-Saloner (1986) model of cyclical changes in firm conduct, and (3) the loss-leader model as formalized by Lal and Matutes (1994).

We document that grocery prices exhibit significant countercyclical pricing over the seasonal cycle. High travel costs between stores and high supermarket concentration ratios at the

local level make it plausible a priori that any of these imperfect competition models could explain pricing dynamics over the cycle. Nonetheless, we find little support for the Warner and Barsky and Rotemberg and Saloner models. In particular, we find that retail margins fall for foods at their seasonal demand peaks, even when the demand peak is an idiosyncratic demand peak for the good rather than an aggregate demand peak for the store. Furthermore, we show that prices do not fall in general at Thanksgiving or Christmas, the two largest aggregate demand spikes and, indeed, if anything appear to rise. Finally, with regards to the Warner and Barsky model, we find no evidence that the elasticity of demand for the products in our sample rises at seasonal demand peaks.

We cannot rule out the Rotemberg and Saloner or Warner and Barsky models altogether because we do not observe all prices in the grocery store. The prices we do observe are not consistent with these models but it is possible that the other unobserved prices exhibit movements consistent with these models. However, this would require, for example, that prices of goods other than tuna and not included in our data set would have to be raised on Lent. In short, the collusive equilibrium would have to be maintained through a complex process of shifting the categories on which prices are coordinated from week to week. This would seem to us to maximize the coordination costs on the part of the retailers.

Finally, the Rotemberg and Saloner and Warner and Barsky models do not rely on advertising prices in any way. Our finding that items with positive demand shocks are advertised at discounted prices requires a different sort of motivating economic force than those present in the Rotemberg and Saloner and Warner and Barsky models of retailer behavior. Instead, we show that the data are more consistent with loss-leader pricing. These models can explain our finding of lower prices for those goods experiencing an idiosyncratic demand peak. Our finding of increases in advertising for seasonally peaking items offers direct support for loss-leader models such as Lal and Matutes (1994) that emphasize the role of advertising. The evidence presented here suggests the importance of the retailer in price determination, a result consistent with the Vrinda Kadiyali et al.

TABLE 7—SEASONAL PATTERNS IN ADVERTISED PRICE SPECIALS

| Panel A: Seasonal Categories    |                               |                                |                              |                               |                              |                               |                              |
|---------------------------------|-------------------------------|--------------------------------|------------------------------|-------------------------------|------------------------------|-------------------------------|------------------------------|
| Variable                        | Beer                          | Eating soup                    | Oatmeal                      | Cheese                        | Cooking soup                 | Snack crackers                | Tuna                         |
| Linear trend                    | 0.52<br>(0.08)                | 0.02<br>(0.01)                 | 0.004<br>(0.02)              | 0.061<br>(0.02)               | 0.02<br>(0.01)               | -0.12<br>(0.02)               | 0.20<br>(0.03)               |
| Quadratic trend                 | -0.00106<br>(0.00002)         | -0.00013<br>(0.00003)          | -0.000008<br>(0.00004)       | -0.0002<br>(0.00004)          | -0.00008<br>(0.00003)        | 0.00014<br>(0.00005)          | -0.0006<br>(0.00006)         |
| Cold                            | 0.039<br>(0.12)               | <b>-0.001</b><br><b>(0.05)</b> | <b>0.18</b><br><b>(0.04)</b> | 0.025<br>(0.067)              | -0.06<br>(0.06)              | 0.32<br>(0.08)                | -0.001<br>(0.11)             |
| Hot                             | <b>0.043</b><br><b>(0.11)</b> | -0.21<br>(0.06)                | -0.04<br>(0.04)              | -0.028<br>(0.069)             | -0.27<br>(0.06)              | 0.04<br>(0.09)                | -0.13<br>(0.12)              |
| Lent                            |                               |                                |                              |                               |                              |                               | <b>9.60</b><br><b>(2.83)</b> |
| Easter                          | 2.60<br>(4.16)                | -3.53<br>(2.02)                | -0.035<br>(1.57)             | 15.6<br>(2.39)                | 2.23<br>(2.11)               | 13.94<br>(3.02)               | 8.49<br>(3.89)               |
| Memorial Day                    | <b>7.41</b><br><b>(4.03)</b>  | -3.17<br>(2.10)                | -0.96<br>(1.66)              | 2.91<br>(2.48)                | -1.43<br>(2.19)              | 3.19<br>(3.13)                | 2.28<br>(4.01)               |
| July 4th                        | <b>10.05</b><br><b>(3.82)</b> | -2.21<br>(2.23)                | -0.41<br>(1.61)              | 1.43<br>(2.63)                | -2.39<br>(2.32)              | 1.21<br>(3.30)                | 8.77<br>(4.52)               |
| Labor Day                       | <b>0.078</b><br><b>(3.72)</b> | -1.48<br>(2.17)                | 3.3<br>(1.57)                | 8.02<br>(2.56)                | 0.65<br>(2.26)               | 5.36<br>(3.22)                | 3.72<br>(4.13)               |
| Thanksgiving                    | -2.35<br>(4.32)               | -3.46<br>(2.04)                | 2.58<br>(1.60)               | <b>8.13</b><br><b>(2.41)</b>  | <b>6.87</b><br><b>(2.12)</b> | <b>8.17</b><br><b>(3.25)</b>  | 2.43<br>(3.92)               |
| Post-Thanksgiving               | -2.06<br>(5.61)               | -5.94<br>(2.73)                | 8.47<br>(2.12)               | 2.90<br>(3.24)                | 10.59<br>(2.85)              | 17.52<br>(4.35)               | -2.75<br>(5.24)              |
| Christmas                       | <b>10.08</b><br><b>(3.50)</b> | -2.49<br>(1.70)                | -1.08<br>(1.32)              | <b>11.03</b><br><b>(2.01)</b> | <b>3.75</b><br><b>(1.77)</b> | <b>33.57</b><br><b>(2.67)</b> | 4.92<br>(3.28)               |
| Constant                        | -13.53<br>(8.08)              | 14.69<br>(1.41)                | 2.35<br>(2.41)               | 14.64<br>(1.66)               | 12.36<br>(1.47)              | 32.91<br>(2.10)               | 13.64<br>(2.71)              |
| Number of weeks                 | 219                           | 387                            | 304                          | 391                           | 387                          | 385                           | 383                          |
| Panel B: Nonseasonal Categories |                               |                                |                              |                               |                              |                               |                              |
| Variable                        | Analgesics                    |                                | Cookies                      |                               | Crackers                     |                               | Dish detergent               |
| Linear trend                    | -0.050<br>(0.01)              |                                | -0.11<br>(0.017)             |                               | -0.095<br>(0.02)             |                               | 0.06<br>(0.02)               |
| Quadratic trend                 | 0.00017<br>(0.00125)          |                                | 0.00021<br>(0.00004)         |                               | 0.00014<br>(0.00005)         |                               | -0.00023<br>(0.00005)        |
| Cold                            | -0.09<br>(0.04)               |                                | -0.068<br>(0.07)             |                               | 0.24<br>(0.089)              |                               | 0.30<br>(0.09)               |
| Hot                             | -0.14<br>(0.0005)             |                                | -0.038<br>(0.08)             |                               | -0.0025<br>(0.093)           |                               | 0.14<br>(0.098)              |
| Easter                          | -5.64<br>(1.56)               |                                | 5.42<br>(2.63)               |                               | -5.06<br>(3.17)              |                               | 2.06<br>(3.39)               |
| Memorial Day                    | -2.09<br>(1.62)               |                                | -0.66<br>(2.72)              |                               | 1.98<br>(3.28)               |                               | 4.14<br>(3.52)               |
| July 4th                        | -0.13<br>(1.71)               |                                | -0.87<br>(2.88)              |                               | 2.50<br>(3.47)               |                               | 0.82<br>(3.72)               |
| Labor Day                       | -0.33<br>(1.67)               |                                | 0.87<br>(2.81)               |                               | 0.83<br>(3.38)               |                               | -5.89<br>(3.63)              |
| Thanksgiving                    | -0.18<br>(1.57)               |                                | -0.66<br>(2.83)              |                               | 7.31<br>(3.41)               |                               | 0.68<br>(3.42)               |
| Post-Thanksgiving               | 4.46<br>(2.11)                |                                | -1.66<br>(3.78)              |                               | 3.03<br>(4.56)               |                               | 2.40<br>(4.59)               |
| Christmas                       | -1.22<br>(1.31)               |                                | -5.81<br>(2.24)              |                               | -6.01<br>(2.81)              |                               | -2.24<br>(2.85)              |
| Constant                        | 11.98<br>(1.08)               |                                | 31.91<br>(1.82)              |                               | 27.87<br>(2.20)              |                               | 10.99<br>(2.00)              |
| Number of weeks                 | 391                           |                                | 387                          |                               | 385                          |                               | 391                          |

Notes: The dependent variable in each column is the percentage of category sales accounted for by advertised specials. Units in the table are percentage points. Bold type indicates periods of expected demand peaks. Standard errors are in parentheses.

(2000) finding on the relative power of retailers and manufacturers.

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