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WHY DON'T PRICES RISE DURING PERIODS OF PEAK DEMAND? EVIDENCE FROM SCANNER DATA

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ABSTRACT

We examine the retail prices and wholesale prices of a large supermarket chain in Chicago over seven and one-half years. We show that prices tend to fall during the seasonal demand peak for a product and that changes in retail margins account for most of those price changes; thus we add to the growing body of evidence that markups are counter-cyclical. The pattern of margin changes that we observe is consistent with "loss leader" models such as the Lal and Matutes (1994) model of retailer pricing and advertising competition. Other models of imperfect competition are less consistent with retailer behavior. Manufacturer behavior plays a more limited role in the counter-cyclicality of prices.

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Introduction

In the textbook model of price determination, in which price is equal to marginal cost, demand-cycle price dynamics are relatively simple. Specifically, if the production function exhibits diminishing returns, prices should rise as demand expands. Thus, if one finds that prices are not rising during a demand boom, some aspect of the textbook model must be incorrect. The first contribution of this paper is to provide evidence that prices do not rise in response to predictable increases in demand, and fall on average in the market we study.

Counter-cyclical pricing could occur when imperfect competition creates a wedge between price and marginal cost. If the size of this wedge is time-varying, then prices might or might not rise in response to a positive demand shock. However, in order to arrive at a specific prediction for how prices move over a demand cycle, one needs to specify the exact nature of the imperfect competition.

To explore these issues we draw on a unique dataset 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% of non-durable 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 dataset allow us to overcome measurement problems that have plagued previous studies of price-cyclicality in imperfectly competitive markets. One advantage of our dataset is the availability of a very accurate time series on the *transactions* 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 cyclicality using data on prices without direct measures of costs. 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 shocks provides a method of discrimination between alternative theories of retailer and manufacturer competition. It is typically difficult to disentangle the price changes resulting from demand shocks from price changes resulting from supplier behavior.

We explore the empirical implications of several types of imperfect competition models in our data. Two main classes of hypotheses based on imperfect competition have been put forth in the literature to explain why markups may be counter-cyclical. First, for example, Bils (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 counter-cyclical. The Bils (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 a fixed cost of searching, it is optimal to search more during high purchasing periods. 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.

Second, counter-cyclical markups may also stem from cyclical behavior in firm conduct. Rotemberg and Saloner (1986) and Rotemberg and Woodford (1991,1992) suggest that markups may be counter-cyclical because tacit collusion is difficult to sustain during booms. Haltiwanger and Harrington (1991) extend this logic to a deterministic demand cycle, such as the seasonal cycle on which we will focus. 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.

We also explore a third model of imperfect competition that focuses on the importance of imperfect information about prices, giving rise to a role for advertising. This model also gives rise to a form of counter-cyclical pricing, although this feature of the model has not been emphasized in the literature. Our formalization of this mechanism is based on Lal and Matutes (1994) and presumes that, if a retailer has to advertise to inform consumers about prices (and pay a fixed cost per ad), then it will be efficient to advertise (and commit to a low price) on the items that are in high demand, regardless of whether the aggregate volume of shopping is high or low. Thus, for example, it pays to deal tuna at Lent and turkeys at Thanksgiving.

In order to explore which of these models of cyclical pricing behavior best conform to our data, we present a simple model that nests three alternative theories of cyclical prices. We highlight the differing empirical predictions of these models. Our ability to apportion price changes into changes in retail margins and changes in wholesale prices will be a crucial input to testing these theories in our data.

Our work is related to empirical work in industrial organization that has focused on testing implications of the Rotemberg and Saloner model. For example, Borenstein and Shepard (1996), for retail gasoline, and Ellison (1994), for railroads, present evidence consistent with Rotemberg and Saloner (1986). In particular, both papers show that, holding current demand constant, prices are lower, the lower is expected future demand. They do not model possibly time-varying elasticities, as suggested by Bils (1987) or by Warner and Barsky (1995). We depart from these papers by testing different implications of the Rotemberg and Saloner model and by explicitly testing this model against alternative models of markup cyclicality.

In the supermarket context, this paper is closely related to MacDonald (2000) and to Hosken, Matsa, and Reiffen (2000). These papers document counter-cyclical movements in supermarket prices over the seasonal cycle. However, these authors did not have access to both retail and wholesale prices and thus, were not able to attribute markup changes to changes in retail behavior, changes in manufacturer behavior, or both. As we explain below, the observation that different models have different implications for retailer and manufacturer margins for different types of goods is at the core of our identification strategy.[1]

Overall, our findings suggest a clear role for retailer behavior in generating counter-cyclical pricing and much less clear evidence of counter-cyclical pricing by manufacturers. However, 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 counter-cyclical pricing in our data. Overall, our findings are most consistent with a loss leader pricing model, such as Lal and Matutes (1994).

The rest of the paper proceeds as follows. In section 1, we present the theoretical framework and identification scheme. In section 2, we describe the dataset and document important features of the supermarket retail environment. In section 3, we show evidence about the seasonality of supermarket prices. In section 4, we examine retail margin behavior and its consistency with the

[1] In spirit, our exercise is close to Ghosal (2000) who attempts to separately check for the impact of cost and demand shocks on markups. Although he uses aggregated, non-transactions prices and considers monetary policy shocks and energy shocks as his demand and supply disturbances.

theories of price fluctuations. Section 5 describes wholesale price changes. Section 6 investigates the Warner and Barsky (1995) model more closely, reporting evidence on changes in the price-sensitivity of purchases at peak demand period. Section 7 investigates the Lal and Matutes (1994) model more closely, investigating seasonal advertising patterns. Section 8 outlines our plans for future research and concludes.

1. Theoretical framework

We will consider three classes of models that may generate counter-cyclical pricing: a model of counter-cyclical collusion, a model of cyclical elasticity of demand, and model of advertising by multi-product firms. All three of these models are roughly 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 slightly extend each of these models to suit better the characteristics of our particular empirical application, and to draw out the more subtle implications of these models, in order to illustrate their differing empirical predictions.

1.1 General framework

We will utilize a single basic set-up to illustrate the predictions of the three classes of models. Consider a Hotelling linear city of length one, with N consumers located uniformly along the city. Retailers A and B are located at the endpoints of the linear city. Each retailer carries two goods, labeled i and j. Depending on the demand state, consumers wish to consume 0,1, or 2 units of each good. We denote the demand state as $Q^D(i,j)$, the quantity demand of good i and good j. In each state in which they demand a good, consumers' reservation price for each unit is R. Consumers bear a travel cost t per unit distance when they travel to a store. The travel cost does not vary with the number of units purchased at the store, although consumers who do not wish to purchase anything at all do not bear a travel cost. Retailers bear a marginal cost c for each unit sold.

To restrict ourselves to the case where firms serve all customers in the city in all demand states, we require $R \geq t/2 + c$.

There are three possible states of demand. In state 1, $Q^D(i,j) = (1,2)$. In state 2, $Q^D(i,j) = (2,1)$ and, in state 3, $Q^D(i,j)=(2,2)$.

1.2 Cyclical elasticity of demand.

Warner and Barsky (1995) consider a model similar to our basic setup sketched above, except they consider retailers selling a single good, the demand for which varies over time. It is easy to see how their results translate to our multi-product context.

Consider demand state 1, where $Q^D(i,j) = (1,2)$. A consumer located at $x \in (0,1)$ is indifferent to shopping at store A vs. store B if:

$$p_i^A + 2p_j^A + xt = p_i^B + 2p_j^B + (1-x)t$$

The total number of customers choosing store A is thus:

$$Nx = N\frac{p_i^B + 2p_j^B - p_i^A - 2p_j^A + t}{2t}$$

Firm A's problem, then, is to maximize total profits with respect to p_i^A and p_j^A

$$Max_{p_i^A, p_j^A} \ \Pi^A = \left(p_i^A + 2p_j^A - 3c\right) N\left(\frac{p_i^B + 2p_j^B - p_i^A - 2p_j^A + t}{2t}\right)$$

Firm A's reaction function is thus:

$$p_i^A + 2p_j^A = (1/2)\,(p_i^B + 2p_j^B + t + 3c) \qquad (1)$$

Notice that the problem is totally symmetric for Firm A and Firm B. Thus, the equilibrium in demand state 1 is characterized by:

$$p_i^A + 2p_j^A = t + 3c \tag{2}$$

Similarly, in demand state 2, the equilibrium is:

$$2p_i^A + p_j^A = t + 3c \tag{3}$$

Finally, in demand state 3, the equilibrium is:

$$2p_i^A + 2p_j^A = t + 4c \tag{4}$$

In all cases, the individual prices for items i and j are indeterminate. This is obvious, given that the consumers' decision of which store to visit depends only on the total price that they will pay, not the individual item prices. Thus, demand states 1 and 2 are effectively identical, the per-item markup charged must *average* t/3 in both states.

However, and this is the main intuition of the Warner and Barsky model, demand state 3 is different from demand states 1 and 2, because aggregate demand is greater in state 3. With the higher demand, the average per item markup must total only t/4, so markups fall in aggregate demand peaks.

The model has no prediction for the relative prices of the various goods offered by the retailer. For each state of demand, many pairs of prices (p_i,p_j) would satisfy the equilibrium condition. In the presence of any costs of adjusting prices, however, the retailer would prefer to change prices as infrequently as possible. Under those circumstances, the retailer may choose prices $p_i=p_j=(t/3)+c$ in demand states 1 and 2, and arbitrarily choose one price to move downward to $(t/6)+c$ in state 3.

Lastly, notice that price is a function of the total quantity purchased *per consumer*; changes in the number of consumers are irrelevant to pricing decisions.

1.3 An Advertising Model

Lal and Matutes (1994) present a model of a multi-product retailer very similar to that which we have outlined, although they do not consider demand cyclicality. In contrast to Warner and Barsky (1995), a main 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, the transportation cost is sunk. Thus, as long as the transport cost between the two stores is large enough, it makes sense for the retailer to charge the consumer's reservation price R for each good. Foreseeing this problem, consumers will not go to the store.

The solution to this conundrum proposed by Lal and Matutes (1994) is price advertising. Advertising serves to commit the retailer to charge particular prices. If advertising were costless, this model basically collapses into the model that we sketched out above: retailers would advertise all of the prices, and the prices would obey the equilibrium conditions that we have sketched out above.

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, R. Lal and Matutes further assume that retailers pay an advertising cost A 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 for R.

Consider the retailer's decision of which good to advertise in demand state 1 in the framework developed above. The retailer is going to extract the same amount of surplus from the consumer regardless of which good is dealt. This means the retailer could charge R for good 2 and t+3c-2R for good 1, or R for good 1 and (t+3c-R)/2 for good 2. Recall, however, that the only restriction that we placed on R is that $R \geq (t + 2c)/2$. Obviously, if there is free disposal, the retailer should avoid negative prices and thus, if $(t+3c)/2 < R < t+3c$, the retailer will advertise the more popular item, item j, and charge R for item i.

This same intuition, that the more popular good is more likely to be advertised, also holds true if the seasonality that we have described occurs because more consumers purchase a particular good during a seasonal boom. Hosken, Matsa, and Reiffen (2000) extend the Lal and Matutes model to this case.

While we couch our discussion in terms of the Lal and Matutes's (1994) setup, separating it from other loss leader models is beyond the scope of this paper. For example, Simester (1995) proposes a signaling model in which advertised prices are somewhat informative about unadvertised prices, as only low-cost firms advertise very low prices. Although not highlighted in Simester's model, with non-negativity constraints on prices, the model requires that the advertised very-low-priced items be items for which demand is fairly high. Thus, we take the Lal and Matutes model as representative of the class of loss leader models.

1.4 Countercyclical collusion models

Up to now, we have only considered the equilibria of static price-setting problems. However, if retailers compete with one another repeatedly, then tacit collusion may emerge. Rotemberg and Saloner (1986) consider tacit collusion in an environment with variable-demand. They show that the temptation to "cheat" will be high during aggregate demand peaks and that only lower markups may be sustainable during these periods of peak demand. Bernheim and Whinston (1990) extend this analysis to a multi-product environment. While their focus is on conglomerates in multiple lines of business, their analysis extends directly to the case of the multi-product retailer.

Tacit collusion is sustained by the threat to revert to the static Nash equilibrium forever if either firm deviates from the collusive solution. Thus, collusion can be sustained as long as:

$$(\Pi^{COLL} - \Pi^{SN})\frac{d}{1-d} \geq \Pi^{DEV} - \Pi^{COLL} \qquad (5)$$

where:

Π^{COLL} = the per-firm profit at the collusive choice of prices.

Π^{DEV} = the profit that a firm can earn via the optimal deviation from the collusive price.

Π^{SN} = the per-firm profit in the static Nash equilibrium.

δ = the rate used to discount the future periods

If R is high enough relative to t, the monopoly price solution upon which the two firms would like to collude is:

$p_i + 2p_j = 3R - t/2$ in demand state 1

$2p_i + p_j = 3R - t/2$ in demand state 2 and

$2p_i + 2p_j = 4R - t/2$ in demand state 3.

(Recall that we have restricted our attention to the case where $R \geq t/2+c$ in order to insure that the entire market is served in all demand states. This is also sufficient to assure that the monopoly prices exceed marginal cost).

A price of $p_i=p_j=R - t/6$, for example, would suffice as a collusive price for both demand periods 1 and 2. A price of $p_i=p_j = R - t/8$ would suffice as a collusive price for demand period 3. Since an optimal solution can be found for each demand state such that $p_i=p_j$, let $p^{M[k]}$ denote the optimal symmetric monopoly prices in demand state k, where $k \in (1,2,3)$. For simplicity, we normalize the retailer's marginal costs to zero for the rest of this example.

Each firm's collusive profit is:

$$\Pi^{COLL[k]} = 3p^{M[k]}/2 \text{ for } k \in (1,2) \text{ and}$$

$$\Pi^{COLL[3]} = 4p^{M[3]}/2.$$

Suppose that firm B is charging the optimally collusive price. The optimal deviation for firm A is given by its reaction functions from equation (1) above:

$$p_i^{A[1]} + 2p_j^{A[1]} = (1/2)(3p^{M[1]} + t)$$

$$2p_i^{A[2]} + p_j^{A[2]} = (1/2)(3p^{M[2]} + t)$$

$$2p_i^{A[3]} + 2p_j^{A[3]} = (1/2)(4p^{M[3]} + t)$$

The deviating firm A's profits, would then equal:

$$\Pi^{DEV[k]} = (1/8t)(3p^{M[k]}+t)^2 \text{ for } k \in (1,2) \text{ and}$$

$$\Pi^{DEV[3]} = (1/8t)(4p^{M[3]}+t)^2$$

When collusion breaks down, the firms will revert to the static Nash solution:

$$\Pi^{SN[k]} = t/2 \text{ for } k \in (1,2,3).$$

We can consider various deterministic seasonal patterns and their potential impact on cooperation. For concreteness, consider the following seasonal cycle: demand state 1, demand state 3, demand state 2, demand state 3, demand state 1, demand state 3, …

We show two important features of this type of demand cycle: [2]

[2] This set-up makes having a low demand state and having a high demand state equally likely, and having the two low demand states equally likely. Obviously, if low demand states were modeled as more common, this would make collusion more difficult to sustain in the high demand states because stealing market share during a boom would be more attractive relative to the presented discounted value of all future profits. Conversely, if high demand states were more common, this would make collusion easier to sustain. If either of the two low demand states were more likely than the other that would also pin down which good to discount.

1. Tacit collusion can support the same prices in demand state 1 and demand state 2 under this seasonal cycle.

2. For some discount rates, tacit collusion can support only lower prices in demand state 3 than it will in demand state 1 or 2.

The first feature is easy to see. Equation (5) implies that the monopoly prices $p^{M[1]}$ are sustainable in demand state 1 as long as:

$$(\Pi^{COLL[3]} - \Pi^{SN[3]})\frac{d}{1-d^2} + (\Pi^{COLL[2]} - \Pi^{SN[2]})\frac{d^2}{1-d^4} + ((\Pi^{COLL[1]} - \Pi^{SN[1]})\frac{d^4}{1-d^4} \geq \Pi^{DEV[1]} - \Pi^{COLL[1]} \qquad (6)$$

Similarly, prices $p^{M[2]}$ are sustainable in demand state 2 as long as:

$$(\Pi^{COLL[3]} - \Pi^{SN[3]})\frac{d}{1-d^2} + (\Pi^{COLL[1]} - \Pi^{SN[1]})\frac{d^2}{1-d^4} + ((\Pi^{COLL[2]} - \Pi^{SN[2]})\frac{d^4}{1-d^4} \geq \Pi^{DEV[2]} - \Pi^{COLL[2]} \qquad (7)$$

If we consider p^M=R - t/6, and p^{SN} = t/3, these conditions collapse for BOTH demand states 1 and 2 to:

$$(2p^{M[3]})\frac{d}{1-d^2} + (\frac{3p^{M[1,2]}}{2} - t)(\frac{d^2+d^4}{1-d^4}) \geq \frac{1}{8t}(3p^{M[1,2]}+t)^2 - \frac{3p^{M[1,2]}}{2} \qquad (8)$$

Thus, if the monopoly solution is sustainable in demand state 1, it is sustainable in demand state 2. This is identical to the logic in Bernheim and Whinston (1990). In a multi-product environment, it is the pooled incentive constraint that matters, not the incentive compatibility constraints for the individual goods. Thus, if the demand shocks to good i and good j are perfectly negatively correlated, as they are in demand states 1 and 2, then regimes 1 and 2 are equally collusive.

Demand state 3, however, has a different incentive compatibility condition. Suppose that the discount rate δ is such that the incentive compatibility constraint in (8) just binds. We show now that the monopoly price is not sustainable in demand state 3.

Incentive compatibility in demand state 3 requires that:

$$(2p^{M[3]})\frac{d^2}{1-d^2}+(\frac{3p^{M[k]}}{2}-t)(\frac{d\ \ +d^3}{1-d^4})\geq\frac{1}{8t}(4p^{M[3]}+t)^2-2p^{M[3]} \tag{9}$$

It is easy to see that the left hand side of Equation (9) is smaller than the left hand side of (8). To see that the right hand side of (9) is larger than the right hand side of (8), one has to insert the optimal monopoly prices for both demand states, given above, into the right hand side.

For the low demand case in (8) case, the deviator's profit less the collusive profit is:

$$\frac{9}{8}(\frac{R^2}{t}+\frac{t}{4}-R) \tag{10}$$

For the high demand case in (9), the deviator's profit less the collusive profit is:

$$\frac{2R^2}{t}+\frac{9t}{32}-\frac{3R}{2} \tag{11}$$

The difference between the "deviation premium" for the high demand case minus the low demand case is thus:

$$\frac{7R^2}{8t}-\frac{3R}{8} \tag{12}$$

Recall again that, in order to restrict ourselves to the case where the entire market is served, we have required $R\geq t/2$. This is a sufficient condition for (12) to be positive. This implies that the right-hand side of equation of equation (9) is greater than the right-hand side of equation (8). If the right hand side of (9) is unambiguously greater than the right-hand side of (8) and the left-hand side of (9) is unambiguously smaller than the left hand side of (8), then it must be the case that, if δ is such that the incentive compatibility constraint at $p=p^{M[1,2]}$ is binding, then $p^{M[3]}$ cannot be supported as a tacitly collusive equilibrium. This is exactly the logic in Rotemberg and Saloner (1986).

Thus, 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.

This unified treatment of the models suggests the following relevant distinctions between their empirical predictions: All the models predict that the prices of high-demand goods will fall during high-demand periods. Where the models show some differences is in their predictions for demand elasticities, and for the behavior of retailer margins for high-demand goods during low-demand periods. 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.

Neither Rotemberg and Saloner (1986), nor Warner and Barsky (1995) predict that retailer margins will fall during these idiosyncratic demand peaks. However, applying the logic of either model to competition amongst manufacturers may predict that *manufacturer* margins will fall during product-specific demand peaks. That is, for example, we might expect that Rotemberg and Saloner 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 Warner and Barsky model and predict that consumers will be more elastic across brands of tuna during Lent, causing manufacturers to lower markups.[3]

Notice that we have ignored models based on increasing returns (even though these models could explain falling prices in booms). We exclude these models for several reasons. First, and most importantly, it seems most likely that if there are any increasing returns they stem

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[3] In this variant, the two endpoints of the linear city would be substitute products by different manufacturers. One could set up the model so that consumers are more likely to bear the costs of engaging in price comparison across brands if these costs are amortized over multiple units.

from some sort of fixed cost (e.g. better use of overhead labor to more efficiently stock shelves or to more quickly process customers at the checkout stand). This sort of fixed-cost can lead to higher profits in booms for the store as average costs fall. But, this will make no difference in pricing decisions unless the number of competitors in the market changes. It seems doubtful to us that at the *seasonal* frequency the number of competitors would change, so the presence of a fixed cost cannot explain falling prices at seasonal demand spikes.

One might instead argue that the increasing returns causes falling *marginal* costs during the aggregate demand peaks. This would matter for pricing. But, with higher crowds in the store and hence more congestion during the booms, what would explain why per-unit costs would fall for the *retailer*? Furthermore, most of the cost savings that one could conceive of for the retailer would be across-the-board cost savings, not cost savings accruing particularly to holiday items. Since we don't have data on all of the prices in the store, we cannot test whether markups rise or fall on average. However, as we discuss below, for the part of the store that we can measure, overall prices are, if anything, higher during the holidays. This casts further doubt on the increasing returns conjecture at the store level.

Finally, one might consider increasing returns for the manufacturers. Again the most plausible cost savings that we can imagine are fixed-cost savings, rather than marginal. Some savings could arise from efficiencies in the distribution system. However, since many of these manufacturers are sending multiple products to the store, these cost cuts should apply to the bundle of goods. We will show that prices of goods with the same manufacturer and presumably the same cost structure often diverge.

For these reasons, we do not consider increasing returns models in our subsequent analysis. For the models on which we do focus, their predictions for various types of goods and demand shocks are outlined in Table 1.

2. Data description and basic facts about Dominick's Finer Foods

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%. Dominick's provided the University of Chicago Graduate School of Business with weekly store-level scanner data by 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; approximately 30% of the dollar sales at DFF are included in the database, we provide details on the specific categories below.

To complement the data on retail prices, we inverted the 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 (p-c)/p). 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's 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 customer count at each DFF store and total sales by department. We will use these data to measure the aggregate level of store traffic. 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.[4]

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/research/mkt/MMProject/DFF/DFFHomePage.html.[5]

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) climatological data from the National Oceanic and Atmospheric Administration on Chicago temperatures -- these data can be found at 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.[6] We used this smoothed mean temperature (TEMP) series to generate two variables:

HOT = max(0, TEMP - 49)

[4] For four weeks in the sample, none of the stores reported data for several days of the week, despite the fact that those stores were open. Because total sales tend to be much higher on weekends than on weekdays, those observations containing only partial weeks were adjusted. So, for example, if the data reported for the week contained Wednesday-Sunday, but not Monday and Tuesday, the data were scaled up by the sample average ratio of full week sales to Wednesday through Sunday sales.

[5] We found that DFF made some errors (in our opinion) in classifying cookies, crackers, and snack crackers. In general, "Crackers" encompasses saltines, graham crackers, and oyster crackers, while "snack crackers" encompasses, Ritz, Wheat thins, Triscuits and other party-type crackers. We reclassified products when there were inconsistencies in what we understood to be DFF's intended scheme. For example, all Snackwells brand chocolate cookies had been classified by DFF as snack crackers; we reassigned them to cookies.

[6] We believe that the expected or average weather conditions matter for our purposes, since given the lead times in promoting items and/or coordinating price changes across the chain there is no way to respond to a short-lived abnormal blip in temperatures.

COLD = max(0, 49 - TEMP)

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) 6 or 8 weeks and found very similar results to those that we report here.

We also generated dummy variables that equal one in the shopping periods before 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 the day of week that different holidays might land on can vary across years, we generate a dummy variable which takes the value one for two shopping weeks before each holiday. For Thursday holidays, then, the variable was set to one for the two weeks prior to the holiday, but zero for the week including the holiday. For holidays taking place on all other days, the dummy variable was set to one for the week before the holiday and for the week including the holiday. We allow the Christmas dummy to remain equal to one 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 one for the 4 weeks preceding the 2 week Easter shopping period. Finally, we construct the variable "Post-Thanks" which takes the value of one for the week following Thanksgiving.

While DFF provides all data to us at the store level, in many cases we will aggregate these data across stores in order to characterize chain-level pricing decisions. Given that DFF uses essentially only 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 Hoch et. al. (1995).

In general, pricing at DFF (and, we believe, at all supermarkets) is characterized by temporary discounting.[7] Prices frequently drop to a temporary sale price and return again to the "normal" price. The path of prices for a typical good (9.5 ounce Triscuit crackers) in our study can be seen in Figure 1. Notice that, during the 7.5 years of our study, Triscuits appear to have only eight “regular prices". Upward deviations from the regular price are virtually nonexistant; temporary downward deviations are frequent.

Total demand at Dominick's is extremely volatile around holidays. Figure 2 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.

A closer view of holiday shopping behavior can be seen in a regression framework. Table 2 presents 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. Easter, Memorial Day, July 4th, Thanksgiving, and Christmas represent statistically significant increases in total sales at DFF. 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

[7] Ariga, Matsui, and Watanabe (2000) show that a similar pattern holds in Japanese supermarkets, see Figure 1. To explain the sales they propose (and find support for) a Pesendorfer-style (1998) dynamic model of price

aggregate spending surges. As seen in Figure 2, the week following Thanksgiving is characterized by a huge, statistically significant decline in sales.

While some holidays constitute times of peak aggregate demand, the seasonal patterns of demand can differ greatly across goods. 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 3.

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 driven by shifts of a demand curve, then we could be mistakenly uncovering movements along the demand curve because of changing prices. Since one goal of our project will be to determine whether prices rise or fall during these demand peaks, this distinction is crucial.

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 potentially allows demand shocks to be confounded with supply shocks. That is, he could be identifying cases where demand is high *because* prices are low.

We will compare the seasonal categories discussed above to a group of goods for which we expect no seasonal demand shifts: analgesics, dish detergent, cookies, and regular crackers (which includes saltines, graham crackers, and oyster crackers).

We can obtain a crude measure of the seasonality of our categories and compare them to the seasonality of the other categories in the Dominick's database. To do this, we regress total category-level quantity sold for each product on a linear and quadratic trend terms, the cold and

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discrimination. However, both papers abstract from the multi-product aspect of the pricing problem that we hot variables, and the dummy variables representing the shopping periods for Lent, Easter, Memorial Day, July 4th, Labor Day, Thanksgiving, Post-Thanksgiving, and Christmas.

One complication to this procedure is that the Dominick's data do not provide category-level quantities. Indeed, quantity is a somewhat ill-defined concept at the category level, given that the items in the category are not all identical. To generate a quantity index, we take the weekly revenues reported by Dominick's for the category, and divide it by a category-level price index series. The price index is constructed using a fixed-weight procedure. Each price is weighted by that item's average market share over the entire time period of the sample.

To assess the importance of the weather and holidays for different categories we present several regressions. The R^2s for a set of baseline regressions including only the linear and quadratic trends are reported in column 2 of Table 4. The next column in the Table reports the incremental contribution to the R^2 that comes from including the temperature variables. The last column in the table shows the incremental contribution to R^2 generated from adding the holiday variables (Easter, Memorial Day, July 4th, Labor Day, Thanksgiving, and Christmas).[8]

The last columns of the table show that are high incremental R^2s associated with the addition of the temperature and holiday dummies in the categories where we expected these periods to be important. There are, however, other categories that also have high incremental R^2s associated with the holidays, which may mean that our *a priori* screen missed some seasonal goods. On closer inspection, however, it appears that most of these are cases driven by the presence of "anti-holiday" goods. For example, this explains the high incremental R^2s associated

emphasize.

[8] This procedure is much cruder than the methodologies that we use below. In particular, we are forced to renormalize the index whenever the price for a UPC is missing. If the missing items are particularly high or low priced, this can disturb the index. We partially address this problem by using size factors to convert the prices into per unit prices.

with the holiday dummies in the cookie and breakfast cereal categories; these goods experience large *declines* in sales at Thanksgiving and Christmas.

The regressions underlying Table 4 also suggest some departures from our *a priori* classifications. Firstly, analgesics, one of our *a priori* non-seasonal 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.

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-aggregate behavior (as we did in Table 4). Both of these avenues have potential pitfalls.

Examining only a few individual UPCs could be misleading due to the multi-product nature of the retailer's problem; retailers may only choose to deal 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 non-representative and could lead one to over- or under-estimate 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 pfeffernuesse 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 dataset. Thus, we move them into a single item aggregate. For each category, we constructed aggregates focusing on the top-ranked UPCs in a category. For all of our categories, we have constructed aggregates that comprise a market share of 30 to 70 percent of the category. The construction of the price aggregates for each category is described in the data appendix.

Constructing the data in this painstaking fashion has allowed us to make some "corrections" to the data. For example, manufacturers often use a separate UPC to denote a "special 75 cents off" package or a "get an extra 2oz free" package types. Typically, when one of these "specials" is introduced, the regular UPC disappears for a few weeks. Then, eventually, the special UPC disappears from the data and the regular one reappears. By clipping these UPC series together, we get a better picture of the relevant price path of the product. This can make a difference to our analyses. For example, in our beer series, the Old Style 24 pack is replaced by a 30-pack at the 24-pack price in most summers.

Using only the UPCs assigned to aggregates will allow us to examine the behavior of individual items. This behavior can be very different across aggregates within a given category. However, to summarize category-level behavior, we will also want some category-level measures. Rather than use the data for the entire category, we construct category-level measures using all of the UPCs that form the aggregates for the category. We do this because these large UPCs tend to be stable without a lot of entry and exit problems and because the items composing the aggregates have been inspected carefully for data continuity problems (like the 24-pack/30-pack Old Style). It would have been impossible for us to conduct these investigations for each of the over 4500 UPCs in the 11 categories that we study.

Table 5 shows regressions using the (log) quantity index for each of our eleven limited categories as the right hand side variables. Of course, the quantity changes for any event are a function of the exogenous demand shift caused by the event and the purchaser's optimal responses to the supply behavior of retailers and manufacturers. Thus, we are hesitant to interpret the results in Table 5 as informative about the relative size of the demand shocks caused by different holidays. Nonetheless, these regressions generally are consistent with our *a priori* hypotheses about demand seasonality.

In interpreting the size of the weather variables it may be helpful to compute the predicted differences at the hottest and coldest weeks (which are about 20 degrees different than the average). By this metric beer consumption around the peak is roughly 30% higher, while oatmeal is roughly 18% higher. Table 5 also reveals the large difference in the pattern of seasonality between eating soups and cooking soups. Sales of cooking soups skyrocket at Thanksgiving, while sales of eating soups have a much smaller movement. Sales of cooking soups are less sensitive to cold weather than sales of eating soups. Furthermore, Table 5 is consistent with our suspicion that Thanksgiving is a bigger demand shock for cooking soups than is Christmas.

3. How do prices move over the demand cycle?

We consider prices at two levels, for item-aggregates and for the overall category. The price of each item-aggregate is constructed by aggregating the prices for each store for each item in the aggregate. The weight assigned to each item's price in the aggregate is the average market share of that item throughout the entire sample period. The weight assigned to each store is also the average market share of that store throughout the entire sample period.[9]

In Table 6, 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 indices 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 right-most column of Table 6. These estimates were calculated by estimating the price equation for each item-aggregate in the category using a restricted Seemingly Unrelated Regression. 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 6.

Table 6 shows that, in general, prices tend to be lower rather than higher during the periods of peak demand for an item. Indeed, thirteen of the fourteen average coefficients

[9] The price index must be renormalized whenever a UPC or store exits the data. However, by selecting large share items that are almost always stocked and by stringing together UPCs when the UPCs are changed, we have attempted to minimize the importance of renormalization on the dataset. Because prices comprising each aggregate are extremely highly correlated, the results using a variable weight price index are (by construction) virtually identical.

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 4^{th} 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. These results are consistent with two possibilities: (1) despite the care we took in attempting to identify demand shocks, we have merely uncovered seasonal patterns in marginal cost, or (2) markups are moving counter-cyclically over the seasonal cycle.

The first hypothesis---seasonal cost patterns that happen to coincide with our *a priori* notions of seasonal demand patterns-- seems particularly unlikely. First, some evidence against this particular hypothesis is identified in a similar setting by MacDonald (2000). He finds that many grocery prices are lower during high purchase months and that during these same months the typical price of the raw agricultural commodities that serve as inputs are usually higher. So at least one important component of costs does not seem to be falling.

Second, the final two panels of Table 6 are highly suggestive that this hypothesis is false. Presumably, the marginal costs of producing and distributing cooking soups and eating soups 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 7 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.

Similarly, in unreported regressions, we examine the holiday price responses of regular 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 crackers prices reported in Table 6, 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% 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.

One important observation about the findings in Table 6 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, the methodology of Table 6 likely understates the importance of seasonal price declines to both retailers and consumers.

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. Thus, under the strong assumption of perfect substitutability, from both the consumers' and retailer's perspectives, holding a sale on one item is identical to holding a sale on all items. Therefore, examining average price responses to a seasonal demand shock for individual aggregates, or even at the category-level using any fixed product weighting methodology, will understate the importance of the price reductions.

To explore the possibility that substitution across items leads to price declines that are effectively larger than those implied by Table 6, we must construct a multi-item index that has varying weights. To do this, we construct a divisia price index for each category using all those items in our aggregates. This index weights each item in the category by that item's market share *in that week*. As one would expect, the variable weight category price index deviates most from a fixed weight category price index when some item in the category has a temporary sale. During a deal, purchases of the temporarily discounted items typically spike, often stealing purchases from other items.

Regression results with variable weight price indices for these constructed categories are contained in Table 7. An inspection of OLS regressions using the aggregated data shows clear evidence of non-normality 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 GLS procedure. The GLS procedure will attain about 95% 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.[10] 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 fourteen 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 five percent level. The magnitudes of the coefficients for most of the holiday variables are

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[10] Specifically, we calculate starting values and then perform Huber iterations (Huber 1964) until convergence followed by biweight iterations (Beaton and Tukey, 1974) until convergence. A description of the procedure can be found in Hamilton (1991).

substantial. Both tuna at Lent and snack crackers and cheese at Christmas have estimated price declines of at least ten percent.

The coefficients for the temperature variables remain small. The coefficient for "hot" for beer implies that, from April 25 when the temperature should be approximately 49 degrees until July 1st, when the temperature should be approximately 74.5 degrees, the price of beer is predicted to fall by 4.8% 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%. For eating soup, the difference between the predicted April 25th price and the price on January 25 (the coldest week of the year, with a predicted temperature of 20 degrees) is 3.8%. Estimated price declines for cooking soup and oatmeal are smaller still, with price declines of 1.2% 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 judgements about the theoretical models. We have found price declines for goods at all demand spikes *for that good*. This finding is inconsistent with price determination being governed solely by the considerations stressed by either Rotemberg and Saloner (1986) or Warner and Barsky (1995) for the retailers. Both are models in which retailers would respond to *overall* increases in demand by cutting prices. Neither model predicts price cuts by the retailer during idiosyncratic demand shocks such as the increase in demand for tuna during Lent. Thus our finding of price cuts during idiosyncratic demand surges runs counter to the predictions of these models.

Also, recall that both of those models of retail competition would predict overall margin cuts during aggregate demand shocks such as Christmas. Of course, in a multi-product environment, those models give no predictions about which products will experience declines in margins. Since we don't have data on every product in the store, we can never reject the hypothesis that margins declined overall at the biggest aggregate demand shock, Christmas. However, we did generate an overall price index containing prices from the 29 categories for which we have data. Regressions using an overall price index (with either variable or fixed weights) suggest that prices are slightly higher at Christmas.

The observation that price declines are far from being pervasive is especially evident for the goods in our study for which we expect no Christmas demand shock. Notice in table 7 that six of these seven prices changes are positive, four of these significantly so at the 5% level. This casts further doubt on the hypothesis that retailer margins are typically declining significantly during these aggregate demand peaks.

These patterns of coefficients 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 Lal and Matutes (1994) and other loss leader models. Retailers are choosing to advertise 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 Rotemberg and Saloner or Warner and Barsky 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.

4. The movement of retail margins over the demand cycle

In principle, the price movements observed in Tables 6 and 7 could be the result of either manufacturer price changes or retailer price changes. To explore this, we use data obtained from DFF for each UPC-week 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. While, we would like to calculate the manufacturer's margins as well, we have no estimates of the manufacturer's marginal costs, and thus, we can only calculate changes in the wholesale price.[11]

Results for regressions using retail margins are found in Table 8. The methodology used here is identical that in Table 7. That is, we use our category-level variable weight price indices to calculate retail margins. This seems most relevant given the Table 7 findings that category-level prices seem to be responding much more than item-level responses (and the 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% level, are found for cheese and snack crackers at Thanksgiving and Christmas, and beer at Memorial Day, July 4th, Labor

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[11] Kadiyali, Chintagunta, and N. Vilcassim (2000) and Chintagunta, Bonfrer, and Song (2000) provide some evidence on this by looking at profits all the way through the distribution channel for several categories. Overall for these categories they find that profits are split roughly half and half between the retailers and manufacturers.

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 shock. Margins on cooking soup actually increase slightly at Christmas, the secondary demand shock.

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% at Lent. This decrease is statistically significant at the one 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 amongst retailers (Rotemberg and Saloner and Warner and Barsky) 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% level for oatmeal and for soup. However, the magnitudes are tiny. The predicted decline in margin is 2.0% from the median temperature week to the coldest week for soup and 1.2% for oatmeal. The predicted decline in margin for beer is less than one percent from the median temperature week to the hottest week.

The results for the non-seasonal goods casts further doubt on the Rotemberg and Saloner and Warner and Barsky models for the retailers. These models would suggest that retail margins at Christmas should be lower on average across all categories. This is impossible to judge given that we don't have data on all categories. However, it is suggestive that at Christmas, the largest aggregate demand shift, retail margins are higher for 6 of the 7 goods that are not expected to have Christmas demand surges. This increase is statistically significant only for eating soup, however.

Altogether, the evidence on retail margins is most consistent with loss leader models such as Lal and Matutes (1994). 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, their model suggests that prices are low on advertised items but the shopper's reservation price is charged for the unadvertised items. Thus, their model has no difficulty with our finding that the margins on non-holiday seasonal items appear to rise on average at Christmas, the largest aggregate demand shock in the dataset.

One further possible explanation for falling retailer margins at both aggregate and idiosyncratic demand peaks is that true marginal cost is falling due to reduction in inventory costs. If the items in our analysis turnover more frequently at the demand peaks than the inventory component of marginal cost will decrease. Of course, it is not obvious that items turnover more rapidly during a demand spike, as retailers may adjust shelf space allocations when the demand for a particular item spikes (such as by allocating "aisle caps" to a 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.[12] The second of these is negligible for the products that we are discussing. How high can the interest cost of turning over an item more quickly be? 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 2 weeks. Both of these assumptions are

[12] 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, is space is not adjustable, the shadow cost of shelf space may be higher than the market rental rate.

biased to make the cost savings look large, as the items in are 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%, the interest cost of carrying inventory is 1% per month. The cost savings of turning over the inventory twice as fast, then, amounts to a savings of about 0.5% over the one-month demand spike. This is small relative to the reductions in margins of about 5% on average that we find at holiday spikes for our goods.

5. The behavior of wholesale prices over the 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 9, we examine changes in wholesale prices over the seasonal cycle. Changes in wholesale prices are generally negative at demand peaks for a good; ten of the fourteen 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 zero at the 5% 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 counter-cyclicality 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 amongst manufacturers, or increased within-category price sensitivity at seasonal demand peaks.

Although all of these explanations are possible, we are disinclined to accept tacit collusion amongst 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 these products are not very well synchronized. For example, the (de-trended) 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 multi-market contact can mitigate the counter-cyclical margins effect identified by Rotemberg and Saloner (1986) if the demand peaks for goods are asynchronous. We illustrate this in our model of retailer behavior above, but the same logic applies to manufacturers. 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% at Christmas, wholesale prices for regular crackers increase a statistically significant 4.3%. If the counter-cyclicality of manufacturer prices is due to countercyclical collusion, then manufacturers must be colluding on a suboptimal product-by-product basis.

6. Seasonal Patterns in Price Elasticity

One clear implication of the Warner-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 dealt. 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, the Lal and Mantutes or Rotemberg-Saloner explanations do not require any seasonal variation in price elasticity. To the extent to which time-varying price elasticities can be measured, we should be able to use this to further discriminate between the Warner-Barsky view and the other explanations.

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

$$\begin{aligned} \ln q_{jt} &= \alpha + \alpha_j + \gamma' s_{jt} + \beta_p \ln p_{jt} + \beta_{thx} \text{Thx} \times \ln p_{jt} + \beta_{xm} \text{Xmas} \times \ln p_{jt} + \\ &\quad \left[\beta_{hot} \text{Hot} \times \ln p_{jt} + \beta_{cold} \text{Cold} \times \ln p_{jt} + \beta_{lent} \text{Lent} \times \ln p_{jt} \right] + \varepsilon_{jt} \qquad (11) \\ &\alpha_j \sim N(0, \sigma_\alpha); \varepsilon_{jt} \sim N(0, \sigma_\varepsilon) \end{aligned}$$

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 10 provides the results of estimation of this random coefficient model. For all categories, estimates of the change in price sensitivity 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 10 provide very little support for the basic mechanism underlying the Warner-Barsky theory. Only 5 of the 22 possible Thanksgiving/Christmas 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 10 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 first assumption seems reasonable in light of the random intercept specification that induces a pattern of correlation across stores.

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 drop at some future date, they might adjust prices. In our situation, we are concerned with the possibility that price endogeneity would bias the price-seasonal demand interaction terms reported in table 10. We are not concerned with biases in the level of price elasticity but in the change in elasticity between the seasonal and non-seasonal periods. Since we include seasonal dummies and temperature variables in (13), the simultaneity problem can arise only if retailers (manufacturers) are exploiting year-to-year variation in the nature of the seasonal demand shocks. That is, retailers can systematically cut prices on Christmas without creating simultaneity bias; 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 simultaneity bias can occur. While we cannot eliminate the possibility that year-to-year changes in the seasonal demand shocks occur, we think it unlikely that these are large compared to the average level of seasonal shocks and the supply shocks that are identifying our model. Moreover, it is hard to imagine that correction for endogeneity bias would change the mixed nature of the results in table 10 in which we observe both large increases and decreases in price sensitivity.

7. Seasonal patterns in advertising

Our results thus far have been very consistent with a "loss-leader" model such as Lal and Matutes (1994). 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. In an effort to more directly corroborate the loss leader models, we explore DFF advertising.

Hosken, Matsa, and Reiffen (2000) confirm this prediction by showing that high demand items are more likely to be placed on sale. In our data set the most popular types of goods are also most prone to be advertised. For instance, among the 31 categories shown in Table 4, there is a positive correlation between category-level sales and the fraction of goods sold on deal.

More significantly, Table 11 confirms that advertising also varies with the seasonal cycle in the accordance with the predictions of the loss leader models. Table 11 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% of the category is put on advertised deal. The main exceptions to the seasonality pattern are the failure of beer to be advertised more in the hot weather than in the median temperature 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.

8. Conclusions and further research

Both the Warner and Barsky (1995) and Rotemberg and Saloner (1986) models have gained currency in the macroeconomics literature as potential explanations for countercyclical pricing. In this paper, we examine a sector of the economy that exhibits 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 either of these imperfect competition models could explain pricing dynamics over the cycle. Nonetheless, we find little support for these models in our dataset. In particular, contrary to the predictions of both models, 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 Christmas, the largest aggregate demand spike and, indeed, appear to rise. Finally, with regards to the Warner and Barsky (1995) model, we find no evidence that the elasticity of demand for the products in our sample rises at seasonal demand peaks.

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 models such as Lal and Matutes (1994) that emphasize the role of advertising in loss leader pricing.

While it remains to be seen whether the effects that we have found have any analogue at business-cycle frequencies, our results at least suggest that retailer is not an neutral pass-through from the manufacturer to the consumer. Since the important contribution of Hall (1988), the literature on measuring markups and markup variation with macroeconomic data has focused on differences in markups across manufacturing industries. For example, Rotemberg and Woodford (1991) examine whether manufacturer concentration ratios are related to the degree of markup cyclicality in final goods prices. However, the price dynamics of final goods may be strongly influenced by the particular retail environments through which those goods pass. Furthermore, it is not obvious that existing evidence from the literature about the behavior of markups will hold constant as the level and type of retail competition is altered by changes in sales technology.

Our paper finds clear evidence that retailers play a role in markup cyclicality. However, we find more mixed evidence on the importance of manufacturers in generating counter-cyclical prices. In subsequent work we hope to look more deeply at manufacturer behavior and attempt to determine whether the extent of the manufacturer response to a demand surge is a function of the structure of the market for the product and the manufacturer's strategic position within that market.

Another direction for future work is to look more closely at the substitution patterns amongst our goods. While it is widely recognized that substitution amongst goods could lead to an upward bias in the cost of living as measured by price indices that allow limited substitution across goods such as the Consumer Price Index, it is difficult to quantify this bias. Since our data provide quantity as well as price data, we are well-positioned to examine the extent of intertemporal and across-good substitution actually induced by the high-frequency price changes that characterize our data.

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Data Appendix:

We used 4 general principles in forming the “aggregates” (i.e. the bundles of UPCs that would be treated as a composite good) within each category. We begin by discussing these principles and then comment on any particularly relevant considerations for each category.

First, we wanted to make sure that the leading items within each category would be included in the analysis. This was done by calculating the market shares of the individual UPCs and then trying to include as many of the top 10 UPCs as possible, subject to the other constraints discussed below.

Second, we chose the groupings so that all pairwise cross-correlations of the price movements within each aggregate would be quite high. Except in the two cases described below, we never bundled UPCs whose cross-correlation was below 0.7. In almost all the aggregates the correlations were above 0.85.

Third, we sought form our aggregates to bundle the UPCs according to a couple of key characteristics. The identity of the manufacturer was always one of the characteristics, and we never aggregated across manufacturers, although we often had several aggregates for the same manufacturer. A second consideration was package size. In most cases we grouped only identical or very similar sizes. When we did use non-identical sizes we sometimes rescaled the prices to move the prices within an aggregate closer together – as explained earlier this can be important if an observation on any of the items in an aggregate are missing. A third factor was the style of the good (e.g. low fat, extra-strength, lemon-scented, etc.). Using just these traits we were able to form aggregates that we believe are both homogenous and simple to describe.

Finally, we used our judgment to make sure that there was some diversity in the selection of items whenever we believed that a category was heterogeneous. In many cases this meant that we sometimes built aggregates that would capture a premium or discount good whose pricing might differ from the market leader. Including these niche items with potentially low market shares meant that we occasionally omitted other potential groupings with higher market shares but whose behavior is likely to have been very similar to the behavior of other aggregates in the analysis.

The following table summarizes the basic characteristics of the items.

Category	# of aggregates	Share of top 10 UPCs	Total category Market share	counts of pairwise upc cross-correlations ≥ 0.85 at store 71
Analgesics	14	8/10	34.8	16/17
Beer	8	10/10	47.8	41/48
Cheese	8	10/10	42.6	62/62
Cookies	9	10/10	29.6	135/171
Crackers	6	9/10	59.4	12/12 (all > 0.95)
Canned Soup	12	9/10	49.4	119/174
Liquid Dish Detergent	8	9/10	38.6	13/19
Hot Oatmeal	6	10/10	69.8	58/58
Snack Crackers	9	9/10	33.8	27/27 (all but 3 > 0.95)
Canned Tuna	7	7/10	52.0	12/12 (all > 0.9, all but 1 > 0.95)

The following particular choices were made for the categories.

Analgesics: The two UPCs within the top ten that are not included were Tylenol 100 count extra strength tablets and Dominick's 100 count coated aspirin. The Tylenol was the 5th largest selling upc, but we already had the 100 count caplet as a solo item in an aggregate and we opted not to have a second solo item aggregate. The Dominick's aspirin was the 10th largest upc, but the only other large-selling Dominick's aspirin was a 500 count bottle and did not want to bundle these two items since the price per tablet was likely to be quite different (which would cause problems when one item or the other was missing.) Instead we formed an aggregate around the 12th largest upc, Dominick's 100 count ibuprofen, which allowed us to bundle caplets and tablets. We also rescaled all of the prices in this category to be on a per-100 count basis.

Beer: All 10 of the top 10 UPCs are included. The cross-correlations within the Miller, Budweiser, and Heineken aggregates are all above 0.97 – in some of these aggregates we opted to exclude 'Ice" beers from the aggregates because the cross-correlations were noticeably lower (even though they may have been above 0.7.) Since the shares of the Ice beers are so low even the weeks where they we being sold this would make little difference to the results. The main difficulty in this category is the treatment of the Old Style aggregate that we described in the text. All but two of the cross-correlations below 0.85 in the category come from the low correlations between the Old Style 24 packs and 30 packs, which co-exist only occasionally.

Cookies: All 10 of the largest UPCs are included. All but two of the cross-correlations that were below 0.85 are in the Pepperidge Farms aggregate that has 17 types of cookies (but still only a total share of 1.4%). We built this aggregate to add diversity to the category. In the Fig Newton aggregate (coo7) we rescaled prices to be on a 16 ounce basis. In the Keebler aggregate (coo5) we rescaled prices to be on an 18 ounce basis. As described below, the Snackwell brand cookies (and several other types of cookies) were classified by Dominick's as crackers. We moved these items into the cookie category and computed market shares according to this expanded definition of the category.

Crackers: Nine of the top 10 UPCs are included. The omitted one is the eighth highest seller and is a small-sized (8 ounce) Nabisco Saltine cracker that did not aggregate with the larger size. We already had several other single item aggregates, two saltine aggregates, and two Nabisco aggregates, so we chose not to include this item.

This category had to be reconstructed from the original Dominick's category because we found a number of inconsistencies in the way in which items were allocated between crackers and snack crackers. For instance, Dominick's put some items with different size packages into different categories. We reviewed all the UPCs in the original Dominick's categories and assigned them to our re-constituted cookie, cracker, and snack cracker categories. The majority of our reclassification involved creating more homogenous categories for crackers and snack crackers. The items transferred to the cookie category were identified based on words like "sweet" or "chocolate" appearing in the description. For instance, all Snackwell's brand cookies had been classified into crackers. The separation between crackers and snack crackers is a little less well-defined. We included saltines, graham crackers and oyster crackers in crackers. All other crackers (Ritz, Triscuit, etc.) were included in snack crackers.

Canned Soup: Nine of the top 10 UPCs are included. The missing one is number 10, a campbell's vegetarian vegetable soup which was not highly correlated with the other campbell's soups. All but 5 of the cross-correlations below 0.85 are in two large campbell's aggregates (campbell's chunky, and campbell's other chicken which have 10 and 13 UPCs respectively.) By skipping the Campbells vegetarian vegetable we made room for a Swanson broth aggregate and a Progresso bean aggregate.

Liquid dish detergent: Nine of the top 10 UPCs are included. The item is the tenth largest seller, 42 ounce Joy Dish Detergent. We excluded this item because it could not be grouped with any of the higher share items and we already had both a 22 ounce Joy aggregate and two 42 ounce aggregates by other manufacturers (Dawn and Ivory). For both the Dawn and Ivory 42 ounce aggregates we included some UPCs that existed for only a few weeks. These UPCs did not have high cross-correlations correlations with the main UPCs in the aggregates, but we included them nonetheless because this seemed to be an artifact of the short period of overlap with the main UPCs. The market share data we use is for this category comes from eliminating all the items in the full detergent category which were intended for use in dishwashing machines. We eliminated these machine detergents based on the manufacturer (cascade, jet dry are always dropped) and the upc description (dropping any items where the description included the words “auto”, “gel”, or “powder”).

Oatmeal: All 10 of the top UPCs are included. By building around these top 10 we are able to capture 70 percent of the market and yet did not have a single cross-correlation in any of the aggregates below 0.85. In the Quaker Instant Oat aggregate (Oat5) we re-scaled the prices to be per 12.5 ounces.

Snack Crackers: Nine of the top 10 UPCs are included. The omitted item is a Ritz Bits Peanut Butter Sandwich which we believed was not actually a snack cracker. We did include several type of crackers with lower market shares (Sunshine Cheeze-its, Pepperidge Farm Goldfish, Keebler Clubs, and Nabisco Socialables) that added diversity to the aggregates. As mentioned above, our snack cracker category was formed by combining the original Dominick’s cracker and snack cracker categories

Canned Tuna: Seven of the top 10 UPCs are included. The omitted UPCs are the 8^{th} through 10^{th} best selling UPCs. The first of these is a 6.12 ounce Star Kist variety, whose prices does not closely co-vary with the other top-selling Star Kist UPCs. Rather than create a second Star Kist aggregate we opted to drop this upc. The 9^{th} and 10^{th} best sellers were large cans (12+ ounces) which did not have any other UPCs that either could be bundled with. We had already included created one single item aggregate of this type using the best-selling large can (12.2 ounce Bumble Bee) so we skipped these UPCs. Instead we formed an aggregate around the 12^{th} best selling item, which was the house brand and could be grouped with several other UPCs to form a relatively large aggregate. The market share statistics we calculated by excluding all of the UPCs in Dominick’s canned seafood category that did not include the word “tuna” in the description.

Cheese: All 10 of the largest UPCs are included. The Dominick’s cheese category also includes sliced cheeses which have a very different seasonal pattern. So we removed any cheeses that had the word “sliced” in the description. The seasonal purchase patterns for the remaining cooking and snack cheeses appeared to be quite similar.

Figure 1

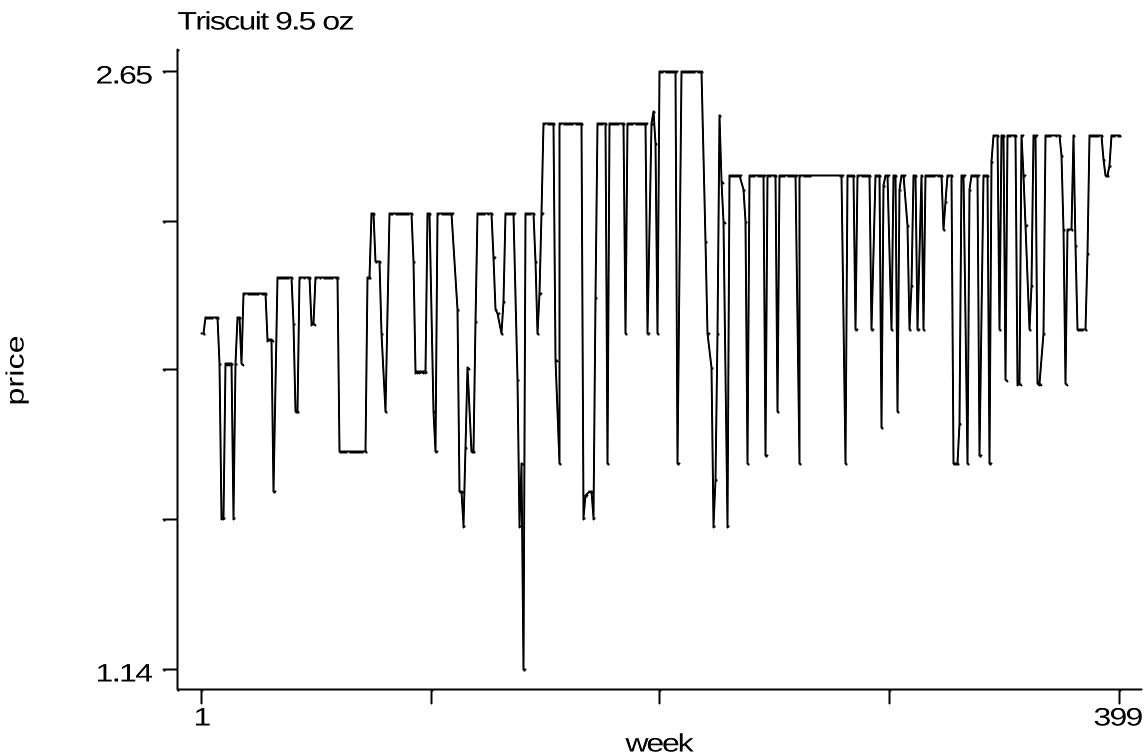

Figure 2

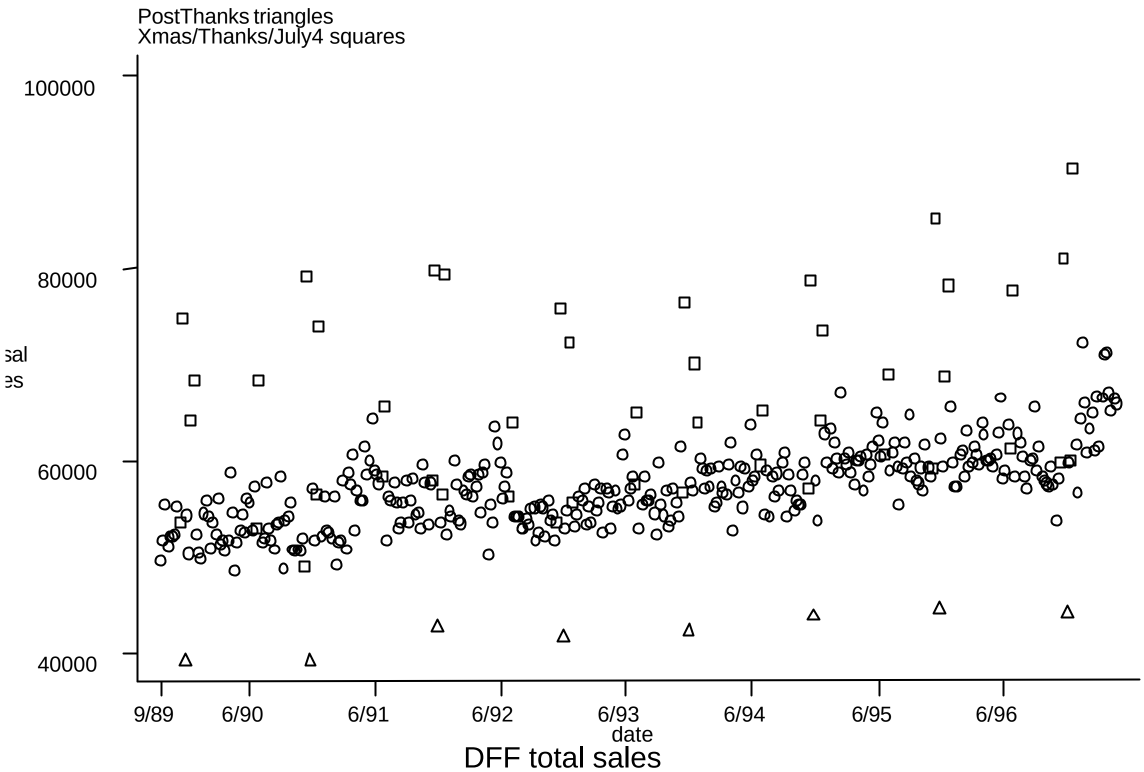
PostThanks triangles
Xmas/Thanks/July4 squares
100000
80000
60000
40000
9/89
6/90
6/91
6/92
6/93
6/94
6/95
6/96
date
DFF total sales

Table 1: Identification Scheme

Candidate Theories	Implied Predictions regarding: Retail margins — aggregate demand spike	Retail margins — idiosyncratic demand spike	Wholesale margins — aggregate or idiosyncratic demand spike	Elasticities — aggregate or idiosyncratic demand spike
Neoclassical demand theory	0/+	0/+	0/+	
Rotemberg & Saloner: Countercyclical collusion				
by retailers	-	0		
by manufacturers			-	
Warner & Barsky: Economies of scale in search				
across retailers	-	0		+
across products within stores			-	+
Lal & Matutes: Advertising	-	-		

Notes:

1) Neoclassical demand theory: The zeros correspond to the possibility of perfect competition with constant returns to scale

2) Rotemberg and Saloner: The idiosyncratic demand shocks should be irrelevant for retailers because they will not initiate price wars unless total spending is high; the negative wholesale margins prediction arises because the demand spikes make it impossible for the wholesalers to maintain collusion.

3) Warner and Barsky: The idiosyncratic demand shocks should be irrelevant for retailers because such spikes do not tempt customers to shop a second store; the wholesalers might cut margins if they believe consumers become more price elastic when buying many units, hence they fight to have their product dealt.

Table 2: Chain Level Pattern of Seasonality at Dominick's Finer Foods

Dependent variable: Log of total sales per store-day. Standard errors are in parentheses.

Linear time trend	0.0002
	(0.0001)
Quadratic time trend	0.0000006
	(0.0000003)
Cold	0.0007
	(0.0005)
Hot	0.0002
	(0.0005)
Lent	0.0056
	0.0130
Easter	0.0637
	(0.0178)
Memorial Day	0.0870
	(0.0184)
July 4^{th}	0.1050
	(0.0194)
Labor Day	0.0312
	(0.0189)
Thanksgiving	0.1590
	(0.0175)
Post-Thanksgiving	-0.2897
	(0.0241)
Christmas	0.1183
	(0.0150)
Constant	10.8682
	(0.0124)
Number of weeks	398

Table 3: Expected Periods of Peak Demand for Different Types of Food

Category	Expected Demand Peaks	Comments
Beer	Hot weather 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 (non-sliced)	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 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 meat eating during this religious period

Table 4: Importance of Holidays and Temperature for Different DFF Categories. Dependent variable: Log quantity sold for all items in a category.

Category	R^2 from a regression containing only a linear and quadratic time trend	Incremental R^2 from adding the hot and cold temperature variables to linear and quadratic time trend	Incremental R^2 from adding dummy variables for holidays to time trend and hot/cold variables
Analgesics	0.397	0.061	0.017
Bath Soap	0.352	0.028	0.022
Bathroom Tissues	0.382	0.003	0.044
Beer	0.067	0.330	0.146
Bottled Juices	0.057	0.033	0.042
Cooking Canned Soup	0.057	0.521	0.088
Eating Canned Soup	0.105	0.473	0.040
Canned Tuna	0.296	0.035	0.006
Cereals	0.027	0.027	0.164
Cheeses (sliced)	0.013	0.056	0.107
Cheeses (party and cooking)	0.029	0.156	0.255
Cigarettes	0.588	0.006	0.020
Cookies	0.042	0.093	0.233
Crackers	0.106	0.093	0.024
Dish Detergent (liquid)	0.191	0.005	0.025
Fabric Softeners	0.816	0.004	0.014
Front-end-candies	0.536	0.047	0.041
Frozen Dinners	0.038	0.053	0.065
Frozen Entrees	0.027	0.035	0.097
Frozen Juices	0.411	0.025	0.034
Grooming Products	0.512	0.105	0.018
Laundry Detergents	0.239	0.001	0.050
Oatmeal	0.010	0.426	0.044
Paper Towels	0.702	0.011	0.018
Refrigerated Juices	0.380	0.033	0.018
Shampoos	0.371	0.036	0.030
Snack Crackers	0.084	0.066	0.285
Soaps	0.670	0.064	0.015
Soft Drinks	0.208	0.016	0.078
Toothbrushes	0.079	0.269	0.060
Toothpastes	0.049	0.045	0.077

Notes: Holidays are Easter, Memorial Day, July 4th, Labor Day, Thanksgiving, and Christmas; see the text for details of how these variables and the temperature variables are defined. Shaded categories are candidates for inclusion in the subsequent analysis.

Table 5: Seasonality patterns for "Categories" constructed from the top-selling UPCs
Dependent variable: Log quantity index, units are percentage points

Coefficient (standard error)	Beer	Eating Soup	Cooking Soup	Oatmeal	Tuna	Snack Crackers	Crackers	Cookies	Cheese	Anal-gesics	Dish Det
Linear time trend	0.27	-0.03	-0.11	-0.42	-0.15	-0.27	-0.05	-0.11	0.222	0.15	0.62
	(0.19)	(0.05)	(0.04)	(0.07)	(0.05)	(0.04)	(0.04)	(0.06)	(0.032)	(0.02)	(0.06)
Quadratic time trend	-0.0005	-0.0004	0.0001	0.0006	0.0000	0.0003	-0.0001	0.0002	-0.0006	-0.0004	-0.0024
	(0.0005)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.00007)	(0.0001)	(0.0001)
Cold	-0.09	1.69	0.75	0.91	0.81	0.34	0.56	0.24	0.29	0.39	0.70
	(0.0027)	(0.23)	(0.18)	(0.16)	(0.24)	(0.16)	(0.16)	(0.27)	(0.14)	(0.09)	(0.26)
Hot	1.52	-1.7	-1.99	-1.55	0.57	-0.32	-1.04	1.14	-0.22	-0.20	0.86
	(0.26)	(0.23)	(0.19)	(0.16)	(0.24)	(0.17)	(0.17)	(0.28)	(0.14)	(0.10)	(0.27)
Lent					49.93						
					(6.12)						
Easter	-8.58	-26.16	12.74	-17.88	1.01	14.37	-20.30	10.63	25.71	-5.58	4.07
	(9.64)	(8.16)	(6.48)	(5.66)	(8.54)	(5.84)	(5.86)	(9.70)	(4.84)	(3.32)	(9.17)
Memorial Day	45.49	-29.71	-27.33	-8.09	-12.96	-5.38	-13.19	1.34	10.72	-2.24	-21.37
	(9.35)	(8.48)	(6.73)	(6.00)	(8.63)	(6.05)	(6.07)	(10.06)	(5.03)	(3.45)	(9.52)
July 4th	37.54	-21.94	-13.43	-3.44	-5.39	23.43	1.66	-18.02	7.77	3.64	-8.50
	(8.86)	(9.00)	(7.14)	(5.82)	(9.11)	(6.39)	(6.41)	(10.62)	(5.31)	(3.64)	(10.06)
Labor Day	25.47	-4.12	3.10	8.48	-3.04	28.09	-3.62	-14.10	10.13	9.44	-18.82
	(8.63)	(8.78)	(6.97)	(5.66)	(8.90)	(6.24)	(6.26)	(10.37)	(5.19)	(3.56)	(9.82)
Thanksgiving	7.09	-6.34	53.68	13.88	-18.16	25.96	8.49	-9.26	13.39	6.79	8.71
	(10.01)	(8.23)	(6.53)	(5.75)	(7.88)	(6.29)	(6.31)	(10.45)	(4.88)	(3.34)	(9.25)
Post-Thanksgiving	28.33	-14.51	-3.03	-3.24	-43.26	11.54	-30.33	-35.48	-14.62	-9.62	-19.94
	(13.02)	(11.05)	(8.77)	(7.65)	(10.49)	(8.41)	(8.44)	(13.98)	(6.55)	(4.49)	(12.41)
Christmas	32.23	-18.55	21.27	-0.20	-39.69	78.42	-18.28	-47.18	62.71	5.78	-7.06
	(8.12)	(6.86)	(5.45)	(4.77)	(6.69)	(5.18)	(5.19)	(08.29)	(4.07)	(2.79)	(7.71)
Constant	1461.78	1393.9	1385.11	1335.12	1274.15	1290.26	1270.52	1306.91	1076.5	1275.57	1264.92
	(18.74)	(5.68)	(4.51)	(8.70)	(5.56)	(4.06)	(4.08)	(6.74)	(3.35)	(2.30)	(6.35)
Number of weeks	219	387	387	304	339	385	385	387	391	391	391

Notes: The construction of the quantity index and the variable definitions are described in the text. Shaded areas indicate periods of expected demand peaks. Standard errors are in parentheses.

Table 6: Estimated price effects at peak demand periods for individual item aggregates
Market shares are share of the total category sales represented by the item are shown at the bottom of each panel. Standard errors are in parentheses. Units are percentage points

Beer

Coefficient (standard error)	Budweiser 24 pack	Miller 6 pack	Miller 12 pack	Miller 12 pack	Miller 24 pack	Heineken 6 pack	Becks 6 pack	OldStyle 24/30 pack	Simple Average	Restricted Sur
Hot	-0.08	-0.01	-0.10	-0.07	-0.02	-0.20	0.02	-0.63	-0.14	-0.17
	(0.59)	(0.10)	(0.09)	(0.10)	(0.06)	(0.09)	(0.11)	(0.08)		(0.03)
Memorial Day	2.07	-4.10	-0.72	-4.46	-0.85	-11.09	-6.29	2.00	-2.93	-0.98
	(2.13)	(3.65)	(3.39)	(3.79)	(2.21)	(3.23)	(4.05)	(2.75)		(1.10)
July 4th	5.72	-1.39	-3.71	-3.31	-4.01	5.72	-4.50	-1.15	-0.83	0.01
	(2.02)	(3.45)	(3.21)	(3.59)	(2.10)	(3.06)	(3.84)	(2.61)		(1.10)
Labor Day	1.80	-1.08	2.34	0.71	-3.39	4.90	-5.05	-2.27	-0.26	-0.56
	(1.97)	(3.36)	(3.13)	(3.50)	(2.04)	(2.98)	(3.74)	(2.54)		(1.10)
Christmas	-2.79	-6.87	-8.05	-2.12	-4.20	-4.46	-6.94	-1.02	-4.56	-3.80
	(1.85)	(3.16)	(2.94)	(3.29)	(1.92)	(2.80)	(3.52)	(2.39)		(1.00)
Market Share	3.9%	4.3%	4.8%	5.7%	16.7%	1.8%	2.2%	8.4%		

Oatmeal

Coefficient (standard error)	Quaker Instant Oats 12-15oz	Quaker Oats 18oz	Quaker Oats 42oz	Quaker Grits 24oz	Regular Cream of Wheat 28oz	Instant Cream of Wheat 12-12.5 oz	Simple Average	Restricted Sur
Cold	-0.24	-0.26	0.002	0.01	-0.01	-0.04	-0.09	-0.006
	(0.13)	(0.11)	(0.04)	(0.04)	(0.02)	(0.07)		(0.02)
Market Share	31.90%	13.50%	10%	2.90%	4.60%	7.10%		

Table 6, continued

Tuna

Coefficient (standard error)	Starkist Chunk 6.12oz	COS Chunk 6oz	Bumble Bee Solid 6.12oz	Bumble Bee Chunk 6.12oz	Geisha 6oz	Bumble Bee Solid 12.2oz	Heritage House Chunk 6.5oz	Simple Average	Restricted Sur
Lent	-8.88	-7.08	-0.51	-8.99	-2.37	-0.85	-5.75	-4.93	-1.9
	(2.65)	(2.55)	(0.97)	(2.93)	(0.97)	(0.54)	(2.08)		(0.42)
Market Share	14.7%	10.1%	4.4%	9.4%	4.1%	3.5%	5.9%		

Snack Crackers

Coefficient (standard error)	Nabisco Ritz 16oz	Nabisco Ritz 11.5-12oz	Nabisco Triscuits 9.5oz	Nabisco Wheat thins 10oz	Nabisco Sociables 8-9oz	Keebler Town House 16oz	Keebler Club 16oz	Pep Farm Goldfish 6oz	Sunshine CheezIt 16oz	Simple Average	Restricted Sur
Christmas	-7.3	0.49	-18.29	-17.96	-18.12	-13.14	1.78	0.35	-5.06	-9.02	-1.700
	(2.16)	(0.90)	(2.61)	(2.52)	(2.51)	(2.88)	(2.05)	(1.51)	(2.17)		(0.65)
Thanksgiving	-2.59	.12	-15.24	-14.84	-15.21	4.24	-4.23	0.32	-6.79	-5.93	-1.400
	(2.62)	(1.10)	(3.18)	(3.07)	(3.06)	(3.50)	(2.50)	(1.83)	(2.63)		(0.79)
Market share	7.9%	2.3%	5.0%	5.2%	3.2%	4.0%	2.0%	2.2%	2.0%		

Table 6, continued

Cheese

Coefficient (standard error)	Kraft Soft Phil Cream Cheese 8oz	Kraft Phil Cream Cheese 8oz	Dominicks Chunk/Block Cheeses 8oz-1lb	Kraft Grated Parmesan 8oz	Dominick's Shredded Cheese 8oz	Kraft Velveeta 32oz	Dominick's Cream Cheese 8oz.	Sargento Shredded 12 oz.	Simple Average	Restricted Sur
Christmas	-14.9	-6.62	-0.45	-3.11	-3.59	-4.56	-5.33	-0.40	-5.51	-2.9
	(2.95)	(1.14)	(1.39)	(1.38)	(3.17)	(1.73)	(2.87)	(1.25)		(0.46)
Thanksgiving	-3.93	-1.84	-1.53	1.12	-3.50	0.36	-6.81	-3.38	-2.30	-1.2
	(3.54)	(1.37)	(1.67)	(1.67)	(3.80)	(2.08)	(3.44)	(1.50)		(0.77)
Market share	3.5%	8.3%	15.7%	2.5%	4.8%	2.7%	2.8%	2.4%		

Table 6, continued

Eating Soups

Coefficient (standard error)	Campbell Tomato 10.75oz	Campbell Chunky Beef/Veg 19oz	Campbell Healthy Request 10.5-10.75oz	Campbell Chicken Noodle 10.75oz	Campbell Chicken 10.5-10.8oz	Progresso Chicken 19oz	Progresso Bean 19oz	Simple Average	Restricted Sur
Cold	0.06	-0.063	-0.03	-0.06	-0.01	-0.07	-0.05	-0.032	-0.052
	(0.09)	(0.05)	(0.05)	(0.07)	(0.03)	(0.06)	(0.06)		(0.02)
Thanksgiving	5.63	4.34	1.98	5.52	0.49	-5.82	2.27	2.06	0.29
	(3.31)	(1.81)	(1.91)	(2.37)	(1.14)	(2.06)	(2.31)		(0.62)
Market share	4.9%	4.5%	3.4%	4.8%	10.1%	2.2%	1.8%		

Cooking Soups

Coefficient (standard error)	Campbell “Cream of” Soups 10.75oz	DFF “Cream of” Soups 10.5oz	Swanson Broths 14oz	College Inn Broths 13.75oz	College Inn Broths 46oz	Simple Average	Restricted Sur
Cold	-0.04	0.02	0.07	-0.06	-0.01	0.00	-0.039
	(0.04)	(0.04)	(0.06)	(0.10)	(0.03)		(0.02)
Thanksgiving	-1.61	-4.22	-5.05	-6.39	-0.26	-3.51	-1.24
	(1.55)	(1.29)	(2.32)	(3.61)	(1.22)		(9.8)
Market share	8.7%	1.0%	2.2%	3.9%	2.0%		

Table 7: Price responses for "Categories" constructed from the top-selling UPCs
Dependent variable: Log of variable weight price index, units are percentage points

Coefficient (standard error)	Beer	Eating Soup	Cooking Soup	Oatmeal	Tuna	Snack Crackers	Crackers	Cookies	Cheese	Anal-gesics	Dish Detergent
Linear time trend	-0.12	0.28	0.30	0.14	-0.03	0.09	0.15	0.12	0.020	0.08	-0.04
	(0.04)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.022)	(0.010)	(0.01)	(0.01)
Quadratic time trend	0.0004	-0.0005	-0.0004	-0.0002	0.0002	-0.0001	-0.0002	-0.0001	-.00005	-0.0001	0.0001
	(0.0001)	(0.00003)	(0.00002)	(0.00003)	(0.00004)	(0.00003)	(0.00002)	(0.0001)	(.00003)	(0.00002)	(0.00003)
Cold	-0.07	-0.13	-0.04	-0.04	-0.11	-0.03	-0.01	-0.07	0.04	0.02	-0.06
	(0.06)	(0.05)	(0.03)	(0.03)	(0.07)	(0.04)	(0.04)	(0.09)	(0.04)	(0.03)	(0.05)
Hot	-0.19	-0.02	0.04	-0.15	-0.08	0.03	0.06	-0.29	-0.05	0.11	-0.09
	(0.06)	(0.05)	(0.03)	(0.03)	(0.07)	(0.05)	(0.04)	(0.09)	(0.05)	(0.03)	(0.05)
Lent					-12.95						
					(1.82)						
Easter	1.84	-0.255	-4.18	-0.90	-0.97	-2.72	3.45	-5.04	-11.82	0.87	-1.14
	(2.07)	(1.76)	(0.98)	(1.13)	(2.54)	(1.56)	(1.41)	(3.24)	(1.57)	(1.07)	(1.62)
Memorial Day	-2.78	2.63	0.87	0.27	1.51	1.92	1.48	2.91	-5.03	-0.19	0.88
	(2.01)	(1.83)	(1.02)	(1.19)	(2.57)	(1.62)	(1.47)	(3.35)	(1.63)	(1.11)	(1.68)
July 4th	-5.09	2.64	0.16	-0.88	2.05	-3.12	2.54	6.18	-3.08	-0.28	-0.99
	(1.90)	(1.95)	(1.08)	(1.16)	(2.71)	(1.71)	(1.55)	(3.54)	(1.72)	(1.17)	(1.78)
Labor Day	-3.85	2.31	1.02	2.35	2.20	-6.60	2.54	5.41	-2.69	-1.81	1.01
	(1.85)	(1.90)	(1.06)	(1.13)	(2.65)	(1.67)	(1.51)	(3.46)	(1.68)	(1.14)	(1.73)
Thanksgiving	-1.04	5.65	-3.60	1.30	5.18	-6.12	-1.19	1.00	-8.27	0.84	-0.99
	(2.15)	(1.78)	(0.99)	(1.15)	(2.35)	(1.68)	(1.52)	(3.49)	(1.64)	(1.08)	(1.63)
Post-Thanksgiving	-3.23	5.17	-2.20	0.17	5.07	-7.92	1.06	2.81	-5.09	1.51	0.94
	(2.80)	(2.39)	(1.33)	(1.52)	(3.13)	(2.25)	(2.04)	(4.66)	(2.13)	(1.44)	(2.19)
Christmas	-2.50	7.28	-0.26	-1.50	5.95	-12.05	3.42	3.48	-10.25	2.05	0.66
	(1.74)	(1.48)	(0.83)	(0.95)	(1.99)	(1.38)	(1.25)	(2.76)	(1.32)	(0.90)	(1.36)
Constant	-306.73	-301.82	-315.83	-209.42	-190.6	-175.51	-225.41	-184.04	108.8	-255.93	-272.89
	(4.03)	(1.23)	(0.68)	(1.73)	(1.65)	(1.08)	(0.98)	(2.25)	(10.89)	(0.74)	(1.12)
Number of weeks	219	387	387	304	339	385	385	387	390	391	391

Notes: The construction of the price index and the variable definitions are described in the text. Shaded areas indicate periods of expected demand peaks. Standard errors are in parentheses.

Table 8: Changes in retail margins for "Categories" constructed from the top-selling UPCs
Dependent variable: Variable weight retail margin, units are percentage points

Coefficient (standard error)	Beer	Eating Soup	Cooking Soup	Oatmeal	Tuna	Snack Crackers	Crackers	Cookies	Cheese	Anal-gesics	Dish Detergent
Linear time trend	-0.21	0.04	0.04	0.04	-0.01	0.01	0.02	0.01	-0.009	0.01	-0.0011
	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.010)	(0.00)	(0.0001)
Quadratic time trend	0.0004	-0.00009	-0.00003	-0.00008	0.00006	0.00002	0.00000	0.00001	0.00006	0.00002	0.0000028
	(0.00007)	(0.00002)	(0.00001)	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00001)	(0.0000002)
Cold	-0.01	-0.07	0.02	-0.04	-0.02	0.00	-0.01	0.01	0.004	-0.02	0.0002
	(0.04)	(0.03)	(0.02)	(0.02)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.0004)
Hot	-0.03	-0.10	-0.05	-0.02	-0.07	-0.03	-0.03	-0.08	-0.08	-0.01	-0.0007
	(0.04)	(0.03)	(0.02)	(0.02)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.0004)
Lent					-5.03						
					(1.06)						
Easter	0.88	0.34	-1.49	0.66	-1.82	-0.39	0.93	-2.71	-2.57	0.92	0.0146
	(1.48)	(1.07)	(0.84)	(0.65)	(1.47)	(1.20)	(1.10)	(1.11)	(1.17)	(0.73)	(0.0139)
Memorial Day	-4.36	1.35	0.42	1.17	-1.16	1.59	0.16	1.84	-0.54	0.08	0.0110
	(1.44)	(1.11)	(0.87)	(0.69)	(1.49)	(1.24)	(1.14)	(1.15)	(1.22)	(0.75)	(0.0144)
July 4th	-4.08	2.18	0.81	0.27	1.82	-1.01	-0.31	1.61	-0.33	0.88	0.0060
	(1.36)	(1.18)	(0.92)	(0.67)	(1.57)	(1.31)	(1.21)	(1.21)	(1.29)	(0.80)	(0.0152)
Labor Day	-2.61	1.42	0.05	0.19	-1.50	-4.61	0.58	1.29	0.27	-0.87	0.0213
	(1.33)	(1.15)	(0.90)	(0.65)	(1.53)	(1.28)	(1.18)	(1.18)	(1.25)	(0.78)	(0.0149)
Thanksgiving	-1.31	1.54	-0.68	0.01	2.27	-5.04	0.73	-1.11	-5.18	-0.51	0.0053
	(1.54)	(1.08)	(0.84)	(0.66)	(1.36)	(1.29)	(1.19)	(1.19)	(1.18)	(0.73)	(0.0140)
Post-Thanksgiving	-3.12	0.87	0.13	-1.25	0.63	-4.54	-0.55	-0.53	-4.15	-1.57	0.0199
	(2.00)	(1.44)	(1.13)	(0.88)	(1.81)	(1.72)	(1.59)	(1.60)	(1.59)	(0.98)	(0.0188)
Christmas	-2.66	2.34	0.51	-0.42	1.00	-8.47	0.40	1.04	-3.23	0.50	0.0116
	(1.25)	(0.90)	(0.70)	(0.55)	(1.15)	(1.06)	(0.98)	(0.95)	(0.98)	(0.61)	(0.0117)
Constant	28.57	18.42	14.21	17.99	25.64	22.84	27.05	24.14	34.38	25.25	0.2709
	(2.88)	(0.74)	(0.58)	(1.00)	(0.96)	(0.83)	(0.77)	(0.77)	(0.81)	(0.50)	(0.0096)
Number of weeks	219	387	387	304	339	385	385	387	391	391	391

Notes: The construction of the margin and the variable definitions are described in the text. Shaded areas indicate periods of expected demand peaks.. Standard errors are in parentheses.

Table 9: Changes in wholesale prices for "Categories" constructed from the top-selling UPCs

Dependent variable: Log of variable weight wholesale price index, units are percentage points.

Coefficient (standard error)	Beer	Eating Soup	Cooking Soup	Oatmeal	Tuna	Snack Crackers	Crackers	Cookies	Cheese	Anal-gesics	Dish Detergent
Linear time trend	0.08	0.23	0.26	0.09	-0.03	0.85	0.11	0.09	0.022	0.08	0.11
	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.012)	(0.01)	(0.01)
Quadratic time trend	-0.00003	-0.00032	-0.00042	-0.00012	0.00015	-0.00014	-0.00019	-0.00011	-0.00001	-0.00013	-0.00032
	(0.00006)	(0.00001)	(0.00001)	(0.00003)	(0.00004)	(0.00002)	(0.00003)	(0.00003)	(0.00003)	(0.00129)	(0.00003)
Cold	-0.02	0.01	-0.05	-0.01	-0.05	-0.04	-0.01	-0.01	0.011	0.02	-0.04
	(0.03)	(0.03)	(0.02)	(0.04)	(0.06)	(0.03)	(0.05)	(0.06)	(0.05)	(0.02)	(0.05)
Hot	-0.16	0.11	0.12	-0.14	0.00	0.06	0.14	-0.07	0.06	0.08	0.03
	(0.03)	(0.03)	(0.02)	(0.04)	(0.06)	(0.03)	(0.05)	(0.06)	(0.05)	(0.02)	(0.05)
Lent					-7.26						
					(1.59)						
Easter	0.80	-0.09	-1.88	-1.77	1.70	-0.64	2.63	-1.20	-4.4	-0.23	-0.67
	(1.17)	(0.91)	(0.79)	(1.25)	(2.18)	(1.12)	(1.65)	(2.14)	(1.81)	(0.80)	(1.75)
Memorial Day	1.93	0.92	0.41	-1.48	3.47	0.31	2.29	-0.07	-3.91	-0.62	1.15
	(1.13)	(0.95)	(0.82)	(1.32)	(2.20)	(1.17)	(1.71)	(2.22)	(1.88)	(0.83)	(1.81)
July 4th	-0.45	0.23	-0.96	-1.33	0.43	-2.69	1.64	1.69	-3.68	-0.59	0.26
	(1.07)	(1.00)	(0.87)	(1.28)	(2.33)	(1.23)	(1.81)	(2.35)	(1.98)	(0.88)	(1.92)
Labor Day	-0.82	-0.39	0.75	2.60	4.00	1.75	2.27	-0.16	-.2.51	-0.92	-0.97
	(1.04)	(0.98)	(0.85)	(1.24)	(2.27)	(1.20)	(1.77)	(2.29)	(1.94)	(0.86)	(1.87)
Thanksgiving	-0.12	2.83	-2.94	2.51	1.63	-0.11	-3.19	1.48	0.73	1.92	-2.11
	(1.21)	(0.92)	(0.80)	(1.68)	(2.01)	(1.21)	(1.78)	(2.31)	(1.82)	(0.81)	(1.76)
Post-Thanksgiving	-0.17	3.72	-3.00	2.51	0.85	-1.45	2.60	2.49	1.91	-0.15	-2.13
	(1.58)	(1.23)	(1.07)	(1.68)	(2.68)	(1.62)	(2.38)	(3.09)	(2.45)	(1.08)	(2.37)
Christmas	0.22	3.11	-0.32	-2.12	3.13	-2.74	4.28	1.71	-2.90	1.08	-1.36
	(0.98)	(0.77)	(0.67)	(1.05)	(1.71)	(1.00)	(1.47)	(1.83)	(1.52)	(0.67)	(1.47)
Constant	-334.53	-322.03	-331.83	-229.53	-219.64	-201.56	-256.44	-211.19	66.53	-284.63	-306.29
	(2.27)	(0.63)	(0.55)	(1.91)	(1.42)	(0.78)	(1.15)	(1.49)	(1.25)	(0.55)	(1.21)
Number of weeks	219	387	387	304	338	385	385	387	391	391	391

Notes: The construction of the Divisia indices and the variable definitions are described in the text. Shaded areas indicate expected demand peaks. Standard errors are in parentheses.

Table 10: Time-Varying Price Sensitivity (standard errors in parentheses)

Category	Price Elasticity	logp x Thx	logp x Xmas	logp x Hot	Logp x Cold	Logp x Lent
Non-seasonal						
Analgesics	-1.87 (.31)	-.24 (.096) 13%	.05 (.07) -3%			
Cookies	-3.6 (.03)	.037 (.12) -1%	-.074 (.11) 2%			
Dish Det	-3.43 (.043)	-1.7 (.19) 49%	-1.1 (.15) 32%			
Crackers	-1.9 (.037)	.16 (.13) -8%	.60 (.10) -32%			
Weather seasonal						
Beer	-5.7 (.023)	.067 (.041) -3%	.31 (.034) -5%	.0011 (.00096) .4%		
Eating Soups	-1.98 (.034)	.043 (.060) -2%	-.14 (.053) 7%		.019 (.0014) -19%	
Oatmeal	-2.93 (.025)	.24 (.075) -8%	.33 (.053) -11%		-.0047 (.0014) 3%	
Holiday seasonal						
Cooking Soups	-2.18 (.03)	-.96 (.045) 44%	-.11 (.039) 5%			
Cheese	-1.2 (.028)	1.2 (.085) -100%	-.66 (.075) 55%			
Snack Crackers	-1.6 (.039)	-1.1 (.10) 69%	-.22 (.098) 14%			
Tuna	-2.2 (.036)	.14 (.090) -6.4%	-.11 (.074) 5%			-.78 (.057) 35%

Table 11: Seasonal patterns in advertised "deals".
Dependent variable: Percentage of category sales accounted for by advertised "deals"

Coefficient (standard error)	Beer	Eating Soup	Cooking Soup	Oatmeal	Tuna	Snack Crackers	Crackers	Cookies	Cheese	Anal-gesics	Dish Detergent
Linear time trend	0.52	0.02	0.02	0.004	0.20	-0.12	-0.095	-0.11	0.061	-0.050	0.06
	(0.08)	(0.01)	(0.01)	(0.02)	(0.03)	(0.02)	(0.02)	(0.017)	(0.016)	(0.01)	(0.02)
Quadratic time trend	-0.00106	-0.00013	-0.00008	-0.000008	-0.0006	0.00014	0.00014	0.00021	-0.0002	0.00017	-0.00023
	(0.00002)	(0.00003)	(0.00003)	(0.00004)	(0.00006)	(0.00004)	(0.00005)	(0.00004)	(0.00004)	(0.00125)	(0.00005)
Cold	0.039	-.001	-0.06	0.18	-0.001	0.32	0.24	-0.068	0.025	-0.09	0.30
	(0.12)	(0.05)	(0.06)	(0.04)	(0.11)	(0.08)	(0.089)	(0.07)	(0.067)	(0.04)	(0.09)
Hot	0.043	-.21	-0.27	-0.04	-0.13	0.04	-0.0025	-0.038	-0.028	-0.14	0.14
	(0.11)	(0.06)	(0.06)	(0.04)	(0.12)	(0.09)	(0.093)	(0.08)	(0.069)	(0.0005)	(0.098)
Lent					9.60						
					(2.83)						
Easter	2.60	-3.53	2.23	-0.035	8.49	13.94	-5.06	5.42	15.6	-5.64	2.06
	(4.16)	(2.02)	(2.11)	(1.57)	(3.89)	(3.02)	(3.17)	(2.63)	(2.39)	(1.56)	(3.39)
Memorial Day	7.41	-3.17	-1.43	-0.96	2.28	3.19	1.98	-0.66	2.91	-2.09	4.14
	(4.03)	(2.10)	(2.19)	(1.66)	(4.01)	(3.13)	(3.28)	(2.72)	(2.48)	(1.62)	(3.52)
July 4th	10.05	-2.21	-2.39	-0.41	8.77	1.21	2.50	-0.87	1.43	-0.13	0.82
	(3.82)	(2.23)	(2.32)	(1.61)	(4.52)	(3.30)	(3.47)	(2.88)	(2.63)	(1.71)	(3.72)
Labor Day	0.078	-1.48	0.65	3.3	3.72	5.36	0.83	0.87	8.02	-0.33	-5.89
	(3.72)	(2.17)	(2.26)	(1.57)	(4.13)	(3.22)	(3.38)	(2.81)	(2.56)	(1.67)	(3.63)
Thanksgiving	-2.35	-3.46	6.87	2.58	2.43	8.17	7.31	-0.66	8.13	-0.18	0.68
	(4.32)	(2.04)	(2.12)	(1.60)	(3.92)	(3.25)	(3.41)	(2.83)	(2.41)	(1.57)	(3.42)
Post-Thanksgiving	-2.06	-5.94	10.59	8.47	-2.75	17.5	3.03	-1.66	2.90	4.46	2.40
	(5.61)	(2.73)	(2.85)	(2.12)	(5.24)	(4.35)	(4.56)	(3.78)	(3.24)	(2.11)	(4.59)
Christmas	10.08	-2.49	3.75	-1.08	4.92	33.6	-6.01	-5.81	11.03	-1.22	-2.24
	(3.50)	(1.70)	(1.77)	(1.32)	(3.28)	(2.7)	(2.81)	(2.24)	(2.01)	(1.31)	(2.85)
Constant	-13.53	14.69	12.36	2.35	13.64	32.91	27.87	31.91	14.64	11.98	10.99
	(8.08)	(1.41)	(1.47)	(2.41)	(2.71)	(2.10)	(2.20)	(1.82)	(1.66)	(1.08)	(2.00)
Number of weeks	219	387	387	304	383	385	385	387	391	391	391

Notes: The construction of the Divisia indices and the variable definitions are described in the text. Shaded areas indicate expected demand peaks. Standard errors are in parentheses.