How do Retailers Adjust Prices?: Evidence from Store-Level Data[1]

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Federal Trade Commission
600 Pennsylvania Ave. NW
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January, 2000

ABSTRACT

Recent theoretical work on retail pricing dynamics suggests that retailers periodically hold sales - periodic, temporary reductions in price, -even when their costs are unchanged. In this paper we extend existing theory to predict which items will go on sale, and use a new data set from the BLS to

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[1]The opinions expressed in this paper are those of the authors and not necessarily the Federal Trade Commission or any of its individual Commissioners. We would like to thank Steve Scutt for his assistance in putting together the data set, and Sara Harkavy and Morgan Long for providing excellent research assistance. We would also like to thank Jim Ferguson and Aileen Thompson for their helpful comments on previous drafts.

I. Introduction

Supermarkets' pricing behavior differs across goods, and over time for many individual goods. Recent empirical studies of retailing behavior have revealed several regularities in retail pricing behavior. First, most retail price changes reflect changes in retail margins, rather than changes in wholesale prices (see Levy et al. [1999]). Second, most price reductions tend to be short-lived (Warner and Barsky [1995], Hosken and Reiffen [1999], Pesendorfer [1997]). Together these findings conform with the casual observation that sales, in the sense of temporary reductions in retail prices that are unrelated to costs, are an important aspect of retailer pricing behavior. Third, sales across various items within a supermarket are substitutes (Levy et al., Hosken and Reiffen) in the following sense. Supermarkets apparently decide to place a group of products on sale each week, and the identity of the specific items to be placed on sale is of somewhat secondary importance. Fourth, the magnitude and frequency of sales differs across types of goods (Lach and Tsiddon [1996], Hosken and Reiffen).

There is existing theoretical research on sales that provides an explanation for some of these pricing patterns. One explanation found in this literature is that sales are a means to intertemporally price discriminate for goods that either are infrequently purchased, or that can be inventoried by consumers (e.g. Sobel [1984]). An alternative explanation is that sales result from retail competition because consumers are heterogenous with respect to store loyalty (e.g. Varian [1980]). Hosken and Reiffen linked these two models to show how multi-product retailers, e.g. grocery stores, behave when they sell multiple goods. One implication of their work is that there should be systematic differences in pricing dynamics among goods based on consumers' costs of inventorying the good.

The goal of this paper is to provide additional empirical evidence regarding empirical regularities in pricing dynamics. The evidence extends previous empirical work and examines some of the predictions of the theoretical work. Our primary data source is a non-public use data set provided to us by the Bureau of Labor Statistics (BLS). This data set consists of 350,097 monthly price quotes on twenty different food items collected from retailers in thirty different metropolitan areas from 1988-1997. A key advantage of using this data set in studying sales is that we can observe a time series of prices on a particular grocery item (e.g. z ounce container of brand x's creamy peanut butter from retailer y) for up to 5 years. Thus, we can examine how often different types of grocery products experience sales.

We establish a number of interesting facts about retail prices in the U.S. First, most products appear to have a "regular price." Using the BLS data, we find that for the 20 categories of products in our sample, products are priced at exactly their annual modal price 62% of the time. Moreover, in every category, products are priced at their annual mode at least 40% of the time. Consistent with Hosken and Reiffen, we also find that when prices are not at their modes, they are overwhelmingly more likely to be below the mode than above it. Second, products appear to go on sale more often when consumer demand is *high* (e.g., eggs before Easter). This is a somewhat surprising phenomenon in that most economists would assume that, other things equal, consumer prices would *increase* during periods of high demand. Third, it appears to be the case that there is substantial heterogeneity regarding which products within a category go on sale; i.e. in each category, certain brands and sizes are far more likely to go on sale than others.

We further explore this last finding using publically-available data provided by A.C. Nielsen, Inc. The advantage of this data is that we can obtain more detailed information on each particular item in the data set than we could using the BLS data. We focus on relating a product's market share (within a category) to the probability a retailer puts it on sale. We find definitive empirical results: forreII.he ae l ally T oa

case, if transportation costs are sufficiently low, consumers will "cream skim", buying some items at each retailer. If consumers behave in this manner, such a strategy by retailer j will be profitable, because retailer j will be selling a larger number of goods at higher margins than retailer i. More generally, the "cream skimming" effect works in the opposite direction as the advertising cost effect, inducing retailers to spread the consumer surplus across multiple goods.

Lal and Matutes [1994] demonstrate in the two product/two firm case that the only equilibria are characterized by both retailers advertising the same good(s) at the same price(s). Any good not advertised will be sold at consumers' reservation value for the good. It follows that in equilibrium no consumer buys from both retailers. When advertising costs are relatively small, then there are three equilibria. In two of the equilibria, a single product is advertised and sold at a price below H (one equilibrium in which each good is advertised). In the third equilibrium, both goods are advertised, and both are sold at less than H. If advertising costs are somewhat higher, but not prohibitive (i.e., not greater than half of consumers' cost of traveling between retailers), the only equilibria feature a single product being advertised and sold at a price below H. They suggest that in a model with more than two goods, all equilibria would feature multiple goods being advertised if advertising costs are sufficiently low.

While Lal and Matutes' equilibria suggests that either (or both) of the two goods may have low

[3]Lal and Narasimhan [1996] also conjecture that more popular items will be featured in the retailer's advertisements.

sense: $*_k$% (k = A,B) of those consumers that derive utility from product k view the products as perfect substitutes, and (1-$*_k$)% do not value j (…k) at all. In addition, the value a consumer places on product A and B are independent of whether they purchase any other good. We assume that ", $, $*_{A,}$ and $*_B$ are the same over the entire Hotelling line.

Within this framework, we would not expect to see a retailer advertise good A and not good B in the symmetric equilibrium. To see the why, consider the extreme case in which everyone who values A values B, but the converse is not true; i.e., $*_A$=1, $*_B$ < 1. In that case, there cannot be a symmetric equilibrium in which A is advertised at a "low" price, but B is not advertised, and priced at H. The reason is that if retailer i deviates by switching the prices and advertising strategies for the two products (i.e., advertise B instead of A), all of the customers who would have would have bought their bundle of goods from retailer i will continue to do so (since their utility is the same from buying A or B). Hence retailer i will retain all of the customers it would have had in the proposed equilibrium. In addition, retailer i will attract customers who value product B but not product A. Therefore, for the same advertising expenditure, a strategy of advertising B instead of A will be a more efficient means of bringing customers to the store (see appendix for the formal proof).

This case is unrealistic, in that it is unclear why a retailer would stock product A at all. However, the intuition holds in the more realistic setting where some consumers like A but not B ($*_A$<1 and $*_B$<1). If a sale on A alone is profitable, then a sale on B alone is more profitable, since B attracts more customers and all customers have the same reservation value. In contrast to the extreme case of $*_A$ = 1, it may be profitable to have both A and B on sale. Given the retailer has product B on sale, the benefit of placing product A on sale is the incremental increase in store traffic that results, "(1-$*_A$). As A and B become more differentiated ($*_{A,}$ $*_B$ become smaller), the retailer will have a greater incentive to place product A on sale as well. Thus, other things equal, we would not expect to simultaneously see sales on products that are very close substitutes. Hence, the prediction of this analysis is that there should be considerable variation in the frequency of sales with a product category; e.g., relatively popular brands of peanut butter have a higher probability of being on sale than relatively unpopular brands. Further, one would not expect to see two brands of products that are very close

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charging a "low" price and potentially selling to non-loyals as well. Varian shows that the only symmetric equilibrium features mixed strategies, where all retailers choose their price from a continuous distribution. Hence, price changes in each period, even though the basic cost and demand conditions do not.

Sobel [1984] combines these two elements in his explanation of sales. In his model, there are multiple retailers, and high-value consumers are not only willing to pay more for the good and are less willing to wait (as in Conlisk et al.), but they also are loyal to one retailer (as in Varian). The primary difference between this model and Conlisk et al. is that while low-value consumers are willing to wait for a low price, they will buy from whichever retailer offers that low price. Hence, an individual retailer may miss the opportunity to sell to the group of low-value/non-loyal consumers because these consumers may have purchased elsewhere. In the multiple retailer model, each retailer faces the same basic decision: Is it preferable to sell to the group of high value customers at a high price, or to cut his price and sell to both these customers and the accumulated low value/non-loyal consumers before a rival does? As the length of time since any retailer had a sale increases, the number of low-value consumers rises as well, and this later option becomes more attractive.

The basic characteristics of the equilibrium in Sobel's model resembles the Conlisk et al. equilibrium. Retailers charge a high price when the number of non-loyal customers is small, but as the number grows, it eventually becomes profitable to reduce price to attract non-loyal customers. The key difference between the monopoly and multiple retailer equilibria is that in the latter case, competing retailers will consider having a sale sooner than a monopolist.[6] Hence, sales occur more frequently (and at deeper discounts) when there are multiple retailers. Another difference is that there will are a range of "sale" prices in the Sobel model. Finally, one can extend the model to show that the difference between the monopoly and multiple retailer cases is a general one. That is, a reduction in the number of competing retailers reduces the frequency and depth of sales, but does not affect the non-sale price of

[6]More precisely, in contrast to the monopoly retailer, with competing retailers the probability that a sale may occur becomes positive as soon as the expected profit from selling to the accumulated low-value consumers at a low price equals the profit from selling to the loyal consumers at their reservation value.

any good.

Hosken and Reiffen [1999] extend the Sobel analysis by considering competition between multi-product retailers. They show that pricing dynamics will differ across goods sold by multi-product retailers; goods which consumers can readily inventory will be characterized by less-frequent, but larger sales than goods which are less readily inventoried. Their model also implies that competition between

[7]One empirical regularity that we do not discuss concerns the use of markdowns. Markdowns differ from the sales in the sense used here in that markdowns refers to price reductions that are not reversed, but rather increase over the course of a fashion season. Pashigian [1988] and Pashigian and Bowen [1991] document this phenomenon for apparel, and show evidence that the extent of markdown is related to the demand uncertainty for the good. Warner and Barsky [1995] provide additional evidence of this pattern, as the only good in their sample that has a fashion element (sweaters) displays this markdown pattern.

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prices is driven by changes in retail margins. As discussed above, the theoretical literature provides two potential explanations for why sales occur. First, firms could be playing a mixed strategy in prices (as in Varian). Second, firms could be using sales to intertemporally price discriminate between high and low value consumers (e.g. Conlisk et. al.). A theory based on the Varian model appears to provide the best explanation of why highly perishable products that are frequently consumed (e.g. milk and eggs) are placed on sale.[9] For easily storable non-perishable products (e.g. ketchup or canned tuna) or infrequently consumed perishable products (e.g. fresh salmon), either the price discrimination or mixed strategy in prices models could describe retail pricing behavior. However, some empirical evidence suggests that consumers "stock-up" during sale period, thus, the price discrimination model may be more appropriate in describing why firms offer sales on non-perishable items.[10] Section V provides some additional evidence regarding the prevalence of sales, and some evidence regarding the characteristics of those products that are put on sale by supermarkets. Section IV describes the data used.

IV. Data Description

This paper identifies and provides an explanation for some empirical regularities in retail price variation. We use two different data sets in our analysis. The first is a non-public use data set we obtained from the Bureau of Labor Statistics (BLS). To our knowledge, this data has not been used in previous academic studies. For this reason, we provide background information on this data source. In collecting the data used to calculate the Consumer Price Index, the BLS samples food retailers in 88 geographic areas, collecting prices of specific items in up to 94 categories of goods.[11] Within each

[9]Because these products cannot be readily stored, firms cannot intertemporally price discriminate against high and low valued consumers of these products

[10]For example, Pesendorfer (1997) finds that seven times as much ketchup is purchased in sale weeks than non-sale weeks.

[11]Where a category is a fairly narrow classification of consumer goods, e.g. cola drinks, eggs, and white bread are BLS categories.

[12]These areas are: Atlanta, Boston, Buffalo, Chicago, Cleveland, Dallas, Dayton, Denver, Detroit, El Paso, Greater Los Angeles, Jacksonville, Kansas City, Los Angeles, Miami, Minneapolis,

Table 1 shows that the observations are fairly evenly distributed throughout the sample period, although some years do have more observations than others. Table 2 presents both the number of unique price series and number of observations for each product category. Our data contains far more information on some grocery products (e.g. ground beef and white bread) than others (e.g. baby food and paper products). This reflects a policy on the part of the BLS to collect more data on products that are viewed as more important in measuring the CPI. Table 3 shows the number of price series and items by geographic area. The sample contains much more information from larger population areas than smaller areas.

Table 4 presents a frequency distribution of the length of the individual price series separately for each product category. As discussed earlier, under the BLS sampling scheme, an individual price series can be as long as 5 years. However, as seen in Table 4, only a small fraction of price series in our sample attain a length of 5 years. In fact, the majority of price series are less than 2 years in length for all product categories except ground beef, eggs, orange juice, and lettuce. According to the BLS, there are two reasons why most of our price series have relatively short lengths.[13] The first reason is that we obtained the same ten calendar years (1988-97) of data for all cities. Because the BLS changes its sample of stores for 20% of its cities each year, 80% of the observations in the first year of our data are part of a series that began in a previous year. Hence, 80% of the observations for 1988

Washington D.C.

[13]Some of the price series have lengths longer than 5 years because the BLS collected an additional year of data for the regions that were rotated out in 1997 for the update of the CPI.

new price series. In the data set, it appears this is the primary reason why most of the time series are so short. For some of the product categories, e.g. canned soup or frozen dinners, this explanation seems plausible. These product categories have many different individual brands and package sizes, and it seems reasonable to believe that the life span of a randomly selected product is short. However, for more stable categories, e.g. cola drinks, we find this explanation less credible. It is well known that there are two major brands of cola (Coke and Pepsi) that come in four different varieties (the permutations of with and without sugar and caffeine) that have been on the market with a commanding market share throughout the sample period. It seems unlikely to us that changes in the product mix would result in 40% of the price series for cola drinks being less than one year in length. The unexpectedly short duration of many of the individual price series appears to be the major shortcoming of the BLS data set. However, while the short length of some of our price series weakens our ability to detect price changes, it does not induce any bias into our analysis.

In order to examine sale behavior, we must operationalize the idea of a sale as a significant temporary reduction in the price of a retail item. We do this by saying that a sale occurs if a product's price falls by some fixed amount in a given period and then rises by a similar amount in the next time period.[14] In many ways, the BLS data is well-suited to measure sales. We typically observe the same product over a relatively long time period and can observe when it experiences a temporary reduction in price. Furthermore, because we have observations on many products for a large cross-section of U.S. cities, we feel confident that our results are robust.

Nevertheless, there are two significant weaknesses in using this data set to determine whether

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[14]We have considered five different price decreases in our definition of sale - 5%, 10%, 15%, 20%, and 25%, although in the interest of brevity, only the results for the 10% and 20% definitions are presented here.

[18]Where a sale as defined as observing at least a certain percentage decrease in a product's price between month t-1 and t, followed by a the same percentage price increase from month t to t+1. Since there is no obvious definition of how large the relevant change has to be, we consider sales of

groups. The results appear in table 7. For *every* product category in our sample the conditional probability of observing a sale is larger, often substantially larger, if the price series experienced a sale within the first 12 months. In fact, in 38 of the 40 hypothesis tests listed there, we reject the null hypothesis with a z-statistic greater than 2.5.[19] For example, as panel a shows, of the 77 cereal price series that experienced a 10% sale within their first 12 months in the sample, 53.2% experienced at least one additional 10% sale in the second 12 months of the sample period, while only 29.2% of the 336 price series that did not experience a sale within the first 12 months experienced at least one 10% sale in the second 12 months. The difference in these conditional proba674 Tc 01mmlsignificonst512 monsecs as me.s408

[19]The corresponding number of z-statistics over 2.5 using all 5 sale definitions was 91 out of 100. Note that for some of the comparisons of conditional probabilities, the number of price series is very small. In these cases it is incorrect to assume that the difference in proportions is approximately normal, and instead we simply interpret the computed z-statistics as measures of the size of the difference between conditional probabilities.

[20]From existing data sources we have found, it is difficult to determine which categories of goods are most popular with consumers. For example, while we can find information on aggregate consumption of peanut butter, however, it is unclear what proportion of people consume peanut butter or given they consume peanut butter, how often they consume it.

popular at certain times in the year; that is, there is seasonal demand for certain products. Of the twenty products in our sample, we identify five which have predictable seasonal changes in demand. The demand for soup increases in the fall and winter (October thru March), peanut butter demand increases as part of back to school planning in August and September, egg demand increases around Easter, and ground beef and hot dog demand increases in the summer (June, July and August). Further, because the costs of producing these items are not seasonal, we are reasonably confident that any change in sale behavior is a result of retailers' reactions to changes in demand rather than supply. Thus, an additional test of the analysis is determining if sales on these products are more likely to occur in periods of high demand. The results of these tests are presented in table 8. Again, the results strongly support the theoretical analysis. We see for any of the sale definitions we consider, retailers are more likely to put these items on sale in periods of high demand, and that these differences are statistically significant in virtually all cases at any standard significance level. Thus, our data suggest that retailers systematically *lower* the prices of items which experience increases in demand. While these results are not surprising to anyone who shops in a grocery store, the analysis presented here provides an explanation for this phenomenon: A retailer attracts a consumer by offering more consumer surplus than its rival does. In order to inform consumers of the surplus that can be obtained, retailers invest resources in advertising sale prices. Thus, other things equal, retailers will choose to put items on sale that are attractive to the widest audience psefhbte;tsaleesubte;tsalaileT consume8T consdythidest ye, sown upw Thupo

Specifically, using the Neilsen data, we regress the probability a product goes on sale on the product's share of revenue within its category. We define a *product* as a particular brand and size of a product (e.g. 18 ounce container of Skippy Creamy peanut butter) and the probability a product goes on sale is the proportion of store weeks that particular size is on sale.[21] Similarly, the market share for a *product* is the share for that specific brand and size, calculated at the city level over the entire time period. Hence, each observation in the data set consists of a product's estimated probability of going on sale and its market share. We estimate this regression separately for each of the seven product categories in the data set (ketchup, tub margarine, stick margarine, peanut butter, sugar, facial tissue, and tuna) and for both cities (Sioux Falls, South Dakota and Springfield, Missouri). For each product, city, and both definitions of a sale (as well as definitions not reported here), we find a positive relationship between a product's market share and the likelihood it goes on sale (see table 9). Further, for Springfield, Missouri for all products but tub margarine, the result is statistically significant at conventional levels, and for Sioux Fall, South Dakota using a 10% sale definition the result is statistically significant for all products except peanut butter. Considering the very small sample sizes in the regression, these results imply that a strongly positive relationship exists.[22]

VI. Conclusion

Several recent papers have provided empirical evidence suggesting that retailer competition results in periodic price changes even when costs are unchanged. However, each of these studies provides evidence about sale behavior for a relatively small number of products from a few retail establishments. This paper attempts to broaden our understanding of these pricing dynamics by providing more systematic evidence about retail prices. Our data covers a large number of products

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[21]Where a sale is defined as before, a temporary price decrease of a given amount followed in the next week by a similar increase.

[22]While these results are consistent with the hypothesis that more popular products are put on sale, it is also consistent with the causality running in the opposite direction; products with lower average prices have greater market shares. In any case, the empirical finding of a positive relationship between the two seems robust.

across a variety of urban areas for a ten year period. Our results suggests that a number of pricing regularities exists for all of these goods. First, for each of twenty categories of goods in our BLS sample, stores seem to have a "regular" price, and most deviations from that price are downward. Second, we find there is considerable heterogeneity in sale behavior across goods in each category; within each category of goods, the same items are regularly put on sale, while other items are rarely, if ever, put on sale. Third, the probability of a sale on an item appears to be greater when demand for that item is highest. Fourth, for the limited number of items for which we know category market shares, there is a statistically significant positive relationship between the likelihood a product is on sale, and its market share.

These latter three observations are consistent with the extension of the Lal and Matutes model presented in Section II. This analysis predicts that relatively popular items should have more frequent sales than relatively unpopular items. More generally, we view this evidence as consistent with the premise that retailers adjust retail prices over time independent of wholesale price changes.

The evidence we have presented here combined with the work of others (both empirical and theoretical) suggests that retail sales are an important component of retail price variation, and that many of the observed instances of sales are consistent with intertemporal price discrimination. Further, these results imply that different types of consumers will effectively face different prices for the products thegests thhply mortail instrumental variables to control for exogenous demand changes) does not correspond to the experiment of changing price and observing the resultant change in quantity along a demand curve. Empirically, the process that causes changes in retail price also causes changes in the position of the demand curve. In particular, as the length of time since the last sale increases, the volume of purchases consumers will make at a particular "low" price increases, and hence so does the retailer's incentive to offer a low price. Correctly measuring demand curves in this type of environment requires explicitly modeling the pricing dynamics (e.g. taking into account past prices in the demand equation).

The observation that effective prices are difficult to measure and vary across individuals implies that researchers should take care when comparing average retail prices. For example, examining the effects of a change in retailing structure (e.g., a merger) on consumers could be quite difficult. The models of sale behavior imply that the effect of a merger is to increase the length of time between sales and raise the expected sale price. This implies that consumers who purchase at the normal price will not be harmed by the merger while the inventorying customers will be. In any event, for products where sales and consumer inventory behavior are important, simply comparing the average prices of a group of items (e.g., pre and post-merger) could be a relatively uninformative measure of harm. Instead, the best way for researchers to examine the effects of changes might be to examine changes in the frequency or depth of sale or changes in shelf price.

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[23]The analysis here can be generalized to n > 3 goods with appropriate reinterpretation of (.

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\begin{cases}
P_B = H \\
P_A = \dfrac{H\gamma(\beta-\alpha)+(1-\gamma)T}{1-\alpha\gamma} \\
P_C = \dfrac{H(\alpha-}{}
\end{cases}
$$

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[24]Note that in the equilibrium derived in Lemma A.1, P_C could be negative. However, most consumers will pay a positive price for the product(s) they buy, since the sum of P_C and either P_A or P_B is positive. Specifically, P_C is more likely to be negative (i.e., negative for a larger range of values for H and T) when ($- ")/(1- ") is large, which is to say, when $ is closer to 1. The closer $ is to 1, the larger the number of customers who are buying a positively-priced bundle. Hence, the condition under which P_C is negative also implies most consumers are buying both C and another good. Moreover, P_C is not literally negative - since we have normalized the retailer's cost at zero, negative "prices" are

$\pi_1 = \gamma \alpha \; x_1[P$

properly interpreted as negative margins. Finally, the possibility of negative margins is not unique to our formulation, negative margins are also possible in Lal and Matutes' model.

$$(1-\gamma)(\beta-\alpha)P_A^1+\gamma(\beta-\alpha)\frac{P_A^1-H}{2}+\gamma\ \frac{H-P_A^1}{2T}(P_C^1+P_A^1)(\beta-\alpha)+(1-\gamma)\frac{H-P_A^1}{2T}(P_A^1)(\beta-\alpha) \quad (3)$$

$$(\beta-\alpha)\ \frac{H-P_A^1}{2T}[-\gamma T+\gamma(P_C^1+P_A^1)+(1-\gamma)P_A^1]$$

using equation (1) we can substitute P_A^1 = T - (P_C^1 into this expression, to show that the term in brackets is equal to (1-()T, and that the expression (3) is equal to

$$(1-\gamma)(\beta-\alpha)\frac{P_A^1+H}{2}.$$

Using the results from Lemma A.1, we see that this expression is positive. That is, it is profitable for retailer 1 to deviate, implying that advertising A and C, but not B can never be an equilibrium. #

It is easy to see that both retailers advertising A
alone is not an equilibrium either. If both retailers were only advertising A, advertising B instead of A would allow retailer 1 to retain all of the customers who would have purchased from him in the initial "equilibrium." Moreover, these customers would pay exactly the same prices as they would have in the initial equilibrium, so that retailer 1's profits from these customers are unchanged (the per-customer expected profits are P_A^1 + (H). In addition, the retailer now earns these same profits from two groups of additional customers; ($-") customers located between retailer 1 and the midpoint of the Hotelling line, and ($-") customers located between the midpoint and the midpoint plus (H - P_A^1)/T (i.e., those customers who are located beyond the midpoint who would receive zero surplus from retailer 2, but get some surplus from retailer 1).#

Table 1: Description of Data Set

by Year

Year	Proportion of Observations
1988	11.4%
1989	10.0%
1990	9.6%
1991	9.9%
1992	10.1%
1993	9.2%
1994	9.3%
1995	10.3%
1996	9.8%
1997	10.4%

Table 2: Description of Data Set

Table3: Descriptive of Data Set

by Region

Region	Number of Price Series	Number of Observations
Atlanta	361	6547
Boston	570	11022
Buffalo	317	5866
Chicago	1765	40019
Cleveland	492	9730
Dallas	536	10657
Dayton	289	6733
Denver	341	6231
Detroit	1069	21404
El Paso	323	7312
Greater Los Angeles	557	15682
Jacksonville	297	7118
Kansas City	374	6033
Los Angeles	1694	35487
Miami	387	7116
Minneapolis	337	6379

San Diego	331	5556
San Francisco	947	25186
Scranton	335	6752
Seattle	355	6566
Syracuse	311	8577
Tampa	280	

[redacted]						

Table 5: Summary of Frequency Distributions of

How Often Price Quotes are at Their Modal Value

Product	Proportion of Time Series at Modal Price less than or equal to 25% of Time	Proportion of Time Series at Modal Price less than 50% of Time	Proportion of Time Series at Modal Price more than 75% of Time	Annual Price Series
Baby Food	0.4%	12.7%	47.3%	790
Bananas	17.6%	42.8%	17.5%	3788
Canned Soup	2.1%	19.7%	39.3%	3570
Cereal	3.2%	21.5%	39.9%	3709
Cheese	6.1%	28.7%	37.5%	3568
Snacks	2.0%	14.1%	50.6%	3074
Cola Drinks	10.3%	34.7%	36.2%	2855
Cookies	4.0%	19.2%	48.6%	1917
Crackers	4.9%	26.3%	35.7%	892
Eggs	48.4%	75.7%	11.1%	4465
Frozen Dinners	1.4%	18.5%	46.0%	1247
Frozen Orange Juice	8.5%	35.0%	24.9%	1672
Ground Beef	7.8%	35.6%	28.2%	3240
Hot Dogs	7.2%	31.9%	36.7%	1274
Lettuce	93.0%	96.6%	1.7%	12213
Margarine	7.4%	31.5%	34.8%	1461
Paper Products	4.3%	19.9%	41.5%	1552

Peanut Butter	5.1%	27.1%	34.3%	1099
Soap and Detergent	4.1%	18.0%	42.5%	2194
White Bread	2.9%	21.5%	56.9%	3063

Table 6: Percentage of Prices Above and Below the Annual Modal Price By Product

	Percentage Above Mode[i]	Percentage Below Mode[i]	Z-Statistic[ii] (P value)
Baby Food	9.5 (592)	16.6 (1032)	3.95 (.0000)
Bananas	14.0 (3371)	28.2 (6791)	15.88 (.0000)
Canned Soup	10.5 (2615)	20.3 (5043)	10.81 (.0000)
Cereal	11.6 (2885)	20.3 (5038)	9.85 (.0000)
Cheese	12.8 (3238)	19.7 (4986)	8.15 (.0000)
Snacks	7.0 (1453)	17.2 (3581)	9.40 (.0000)
Cola Drinks	10.5 (1872)	23.5 (4184)	11.80 (.0000)
Cookies	7.8 (1049)	18.6 (2491)	8.09 (.0000)
Crackers	7.8 (516)	25.7 (1699)	8.66 (.0000)
Eggs	25.6 (5795)	32.4 (7346)	8.55 (.0000)
Frozen Dinners	7.8 (552)	21.6 (1531)	7.24 (.0000)

Frozen Orange Juice	12.3 (1560)	27.5 (3479)	11.86 (0000)
Ground Beef	11.8 (2996)	25.6 (6480)	15.22 (0000)
Hotdogs	10.2 (908)	24.3 (2170)	8.92 (0000)
Lettuce	18.2 (4206)	65.0 (15007)	53.84 (0000)
Margarine	11.1 (1222)	23.4 (2576)	8.95 (0000)
Paper Products	9.2 (602)	22.3 (1454)	6.94 (0000)
Peanut Butter	11.5 (984)	22.2 (1904)	7.03 (0000)
Soap and Detergents	8.7 (832)	20.8 (1996)	7.79 (0000)
White Bread	10.6 (2462)	18.0 (4183)	8.11 (0000)

i Number of observations in parentheses.

ii P-Values in parentheses.

Table 7 - Percent of Price Series Experiencing at Least One Sale in the Second Year of the Sample, Conditional on Whether there is a Sale within the First Year

Panel a - sale = 10% reduction

Product	Conditional on at least one sale within the First Year (number of price series)	Conditional on no Sale within the First Year (number of price series)	Z-Statistic (p-value)
Baby Food	26.7% (15)	3.7% (82)	3.17 (.0016)
Bananas	84.0% (401)	52.9% (87)	6.41 (0)
Canned Soup	51.8% (110)	17.4% (265)	6.81 (0)
Cereal	53.2% (77)	22.0% (259)	5.29 (0)
Cheese	56.1% (139)	21.0% (257)	7.07 (0)
Snacks	68.5% (124)	25.8% (151)	7.08 (0)
Cola Drinks	72.0% (157)	25.4% (122)	7.72 (0)
Cookies	66.7% (63)	20.0% (115)	6.18 (0)
Crackers	84.9% (53)	25.5% (51)	6.10 (0)

Eggs	63.5% (244)	38.5% (218)	5.37 (0)
Frozen Dinners	60.9% (46)	34.2% (38)	2.43 (.015)
Frozen Orange Juice	64.6% (113)	36.4% (118)	4.28 (0)
Ground Beef	70.3% (246)	36.1% (216)	7.37 (0)
Hot Dogs	65.1% (83)	37.5% (56)	3.20 (.0014)
Lettuce	96.1% (417)	70.0% (40)	6.59 (0)
Margarine	66.2% (74)	32.1% (109)	4.54 (0)
Paper Products	76.5% (17)	32.3% (31)	2.93 (.0034)
Peanut Butter	49.0% (51)	17.4% (109)	4.17 (0)
Soap and Detergent	64.5% (31)	21.2% (33)	3.51 (.0004)
White Bread	60.9% (151)	15.0% (233)	9.34 (0)

Panel b - sale = 20% reduction

Product	Conditional on at least one Sale within the First Year (number of price series)	Conditional on no Sale within the First Year (number of price series)	Z-Statistic (p-value)
Baby Food	50.0% (2)	3.2% (7)	3.29 (0.0012)
Bananas	72.4% (333)	49.0% (155)	5.03 (0)
Canned Soup	32.0% (50)	10.8% (325)	4.08 (0)
Cereal	54.5% (44)	14.7% (292)	6.16 (0)
Cheese	44.0% (75)	13.1% (321)	6.15 (0)
Snacks	56.8% (88)	23.0% (187)	5.53 (0)
Cola Drinks	52.8% (108)	17.5% (171)	6.19 (0)
Cookies	44.8% (29)	13.4% (149)	3.98 (0)
Crackers	60.0% (35)	25.0% (64)	3.57 (.0004)

Eggs	49.6% (121)	15.5% (341)	7.48 (0)
Frozen Dinners	60.0% (35)	16.3% (49)	4.15 (0)
Frozen Orange Juice	56.5% (85)	24.7% (146)	4.85 (0)
Ground Beef	54.6% (130)	21.1% (332)	7.04 (0)
Hot Dogs	52.7% (55)	32.1% (84)	2.42 (.0156)
Lettuce	83.0% (358)	71.7% (99)	2.50 (.0124)
Margarine	54.8% (42)	18.4% (141)	4.67 (0)
Paper Products	50.0% (6)	21.4% (42)	1.51 (0.131)
Peanut Butter	28.6% (21)	5.8% (139)	3.45 (.0006)
Soap and Detergent	42.9% (14)	10.0% (50)	2.88 (.004)
White Bread	44.1% (102)	12.1% (282)	6.86 (0)

Table 8: Probability of Sale for Various /

Products in Relatively High and Low Periods of Demand

Panel a - Sale = 10% reduction

Table 9 - RELATIONSHIP BETWEEN PROBABILITY OF A SALE ON A PRODUCT AND ITS CATEGORY MARKET SHARE

Panel a: Sioux Falls, Sale =10 %

Product	Intercept		Market Share		P Value for Slope Coef.	R-squared	Obs.
	Estimate	Error	Estimate	Error			
Ketchup	0.0023	0.0038	0.0022	0.0004	0.0001	0.6843	15
Margarine -	0.0161	0.0096	0.0047	0.0009	0.0003	0.7073	13
Margarine -	-0.0045	0.0044	0.0045	0.0007	0.0001	0.6673	20
Peanut Butter	0.0142	0.0074	0.0029	0.0020	0.1681	0.0692	29
Sugar	0.0067	0.0077	0.0050	0.0018	0.0129	0.3120	19
Tissue	0.0180	0.0076	0.0050	0.0019	0.0177	0.2299	24
Tuna	0.020	0.012	0.002	0.001	0.0333	0.350	13

[redacted]

Table 9 - (con’t)

Panel c: Sioux Falls, Sale = 20 %

Table 9 - (con't)

Panel d: Springfield, Sale = 20 %

Product	Intercept		Market Share		P Value for Slope Coef.	R-squared	Obs.
	Estimate	Error	Estimate	Error			
Ketchup	-0.0022	0.0017	0.0016	0.0002	0.0001	0.7254	19
Margarine -	-0.0046	0.0020	0.0031	0.0002	0.0001	0.9308	17
Margarine -	0.0014	0.0016	0.0002	0.0004	0.6909	0.0055	31
Peanut Butter	-0.0018	0.0021	0.0025	0.0004	0.0001	0.5974	24
Sugar	0.0080	0.0107	0.0042	0.0015	0.0197	0.0197	12
Tissue	0.0068	0.0053	0.0034	0.0012	0.0032	0.3598	22
Tuna	0.0070	0.0037	0.0019	0.0003	0.0001	0.7497	17