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On the Frequency, Depth, and Duration of Sales at High–Low Pricing Supermarkets

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ABSTRACT

This study examines the phenomenon of advertised sales, or price discounts, at major high–low pricing (HLP) supermarkets in the United States. The authors measure and document price variability and movement using a unique and rich dataset on prices and sales drawn directly from supermarkets. Several of their key findings pertain directly to an influential study by Hosken and Reiffen (2004) on retail price variation. However, the authors' estimate of price rigidity is lower than Hosken and Reiffen's while their estimate of sale frequency is higher. Moreover, the earlier study's key findings apply only to national brand products and not private labels. The authors also highlight the issue of sale duration, indicating that sales frequently run considerably longer than 1 or 2 weeks, to the point at which they argue they can no longer be considered temporary price reductions. Comparisons with alternative definitions of sale reveal that the empirical definition of a sale impacts the results significantly. [EconLit Citations: D220, D400, L200]

1. INTRODUCTION

Advertised sales, or temporary and advertised reductions in prices, have become a major component of food retailing in the United States.[1] They are the cornerstone of the high–low pricing (HLP) strategy, also referred to as Hi-Lo or PROMO in the literature, which is prevalent among U.S. supermarkets. Under HLP, supermarkets apply discounts to a subset of products that typically changes once per week. The discounts are then advertised in flyers and increasingly on the Internet. Sales are very widespread in food retailing. Ellickson and Misra (2008) showed that 34% of all supermarkets in the United States utilize storewide HLP, whereas another 38% feature HLP in selected departments. In a 2007 survey of U.S. supermarkets conducted by the University of Minnesota Food Industry Center, 63% of all supermarkets classified themselves as HLP. NielsenWire (2009) reported that, as of 2009, American food shoppers purchase 42.8% of all products on some form of promotion, or temporary discount.

Sales have been examined from many different angles in the economic and marketing literature. The following list is by no means comprehensive. Blattberg, Briesch, and Fox (1995) reviewed the literature on the motivations retailers have for offering discounts as well as their effects on quantities sold. Villas-Boas (1995), Leeflang and Wittink (1996), and Steenkamp, Nijs, Hanssens, and Dekimpe (2005) expanded the discussion of motivation to include competitive considerations. Kaul and Wittink (1995), Mela, Gupta, and Lehmann (1997), and Nijs, Dekimpe, Steenkamp, and Hanssens (2001) discussed sales in the context of brand loyalty and equity. Tellis and Zufryden (1995) and Besanko, Dube, and Gupta (2005) studied the rate at which retailers pass the discounts they receive from wholesalers on to consumers. Gupta (1988), Deighton, Henderson, and Neslin (1994), and Narasimhan, Neslin, and Sen (1996) all examined the relationship between sales and consumer stockpiling.

The breadth of research on the topic is a testament to the importance of sales in food retail. However Hosken and Reiffen (HR; 2004) is the only study of which we are aware that was

[1]The term "sale" as used in this paper refers strictly to price discounts and not to quantity sales or disappearance.

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conducted to understand the prevalence of sales and their role in determining price variation. To test the sale patterns of supermarkets against existing pricing models or to formulate a new model to describe retailer behavior, we first need an understanding of several key variables measuring sales activity. These include frequency, depth, and duration, all of which may vary across departments or product categories within stores.

A solid, empirical understanding of sales pricing behavior among the supermarkets that most commonly use them can be instrumental in testing and applying models of the effects of sales such as those referenced above. Moreover, we are motivated to study and understand sales for two longer-term goals in economic research that are beyond the scope of this study. One is to formally link sales pricing with variability in farm prices, incomes, and welfare. HR uncovered the potential for sales to increase price variability, which in turn may have effects upstream with respect to market clearing for raw commodities. The other is to connect sales pricing and competition through the timing of sales, both interstore and intrastore, with price effects and product innovation.

We reexamine and expand upon the work of HR using a unique dataset that overcomes the major shortcomings of their dataset. Our data consists of weekly, rather than monthly, prices and sales that come directly from two major supermarket chains. Hence, unlike HR, we are able to attribute all prices and sales to specific stores. We are able to identify the exact products for which we have prices. Perhaps most importantly for this analysis, in our data all sales are labeled and defined, leaving no ambiguity as to whether or not changes in price can be attributed to sales. Although HR defined sales in their data based on previously asserted assumptions about sales drawn from economic literature, we examine sales as defined by the stores themselves.

Overall, several of HR's overarching findings hold up reasonably well. We attribute our differences with their results to three main factors: (a) The definition of a sale, as used by HR, differs considerably from observed, store-defined sales, (b) the fact that they aggregate over several chains that may not use HLP or may change their pricing strategies during the lengthy time series (10 years) of their data, and (c) the different time periods of the datasets, as our data are much more recent (2008–2010), and the supermarket industry has undergone substantial change in the past two decades. With respect to HLP stores, we find that the prevalence of sales and the impact of sales on price variability are greater than those found by HR. Moreover, the extent to which prices remain fixed, even after controlling for sales of sufficiently long duration as to no longer be considered temporary price discounts, is lower among current HLP stores.

New insights drawn from this study pertain to the duration of sales, showing that most advertised sales last longer than one week and that certain products are on sale more often than they not. This raises important questions about the applicability of store-defined sales in today's retailing landscape to both classic economic pricing models and the motivations for conducting sales that are espoused and cited frequently in the marketing literature. We demonstrate that the manner in which sales are defined can have major impacts on studies of food retail price variation. We also examine sales pricing activity as it varies across all major supermarket departments and between national brands (NBs) and private labels (PLs), in an effort to clarify the results of complex decisions made in setting prices.

2. DATA AND STORE INFORMATION

Our dataset consists of weekly prices for two major supermarket chains, Chain A and Chain B. Both chains operate primarily in the western United States, though Chain A has stores in selected eastern metropolitan areas. The chains' respective corporate websites make prices transparent where the firms offer online retail. Through online retail, consumers are able to select and pay for their groceries and then have their selections delivered to their homes, or in certain cases, bundled for in-store pickup. The data were collected on a monthly basis from March 2008 through August 2010, using an automated computer program. The program input zip codes for which Chains A and B offered online retail, then recorded all prices and sales for those zip codes.

TABLE 1. The Cities Sampled

City	Zip code	Chain	Population	Median household income ($)
Boise, ID	83705	Chain B	185,787	42,432
Palm Springs, CA	92262	Chain B	42,807	43,800
Salt Lake City, UT	84101	Chain B	178,858	37,287
Los Angeles, CA	90023	Both	3,849,378	42,667
Las Vegas, NV	89103	Both	478,434	47,863
Portland, OR	97213	Both	537,081	42,287
San Diego, CA	92114	Both	1,256,951	55,637
Seattle, WA	98101	Both	582,424	49,297
Vancouver, WA	98660	Chain A	158,855	40,743
Sacramento, CA	95815	Chain A	453,781	44,867
San Jose, CA	95113	Chain A	929,936	70,291
San Francisco, CA	94102	Chain A	744,041	57,496
Washington, DC	20001	Chain A	581,531	47,221
Tucson, AZ	85701	Chain A	518,956	34,241
Philadelphia, PA	08026	Chain A	1,448,394	32,573
Baltimore, MD	21075	Chain A	631,366	32,456
Fresno, CA	93650	Chain A	466,714	37,800

Source: Estimates from the U.S. Census, 2005.

The data cover all products offered online by both chains and therefore include the majority of all products available for sale. The major exceptions from data coverage include alcohol and tobacco products, large general merchandise items, greeting cards and magazines, seasonal decorations, some bakery and delicatessen offerings, certain specialty and niche products, and certain new products.

Table 1 shows the metropolitan regions home to the stores sampled for this study, selected due to the presence of online retail at the start of the data collection period. Although intercity variations in retail prices are not a focus in our work, Table 1 provides some statistics to demonstrate that our data come from cities that range from small (Palm Springs) to large (Los Angeles) as well as low income (Baltimore) to high income (San Jose). Our findings are intended to describe food retail in general and not to any particular slice of America. In many cases, both chains operate in these pricing zones; however, only one offered online retail as we collected our data.

Table 1 references the cities by a single zip code, despite the fact that most of these cities have several zip codes within their geographic limits. To use the corporate websites to shop online, or in our case obtain data, one must input zip codes. One potential issue with our data is that prices or sales may vary within cities, across neighborhoods as defined by zip codes. Conversations with professionals from both chains, as well as our own sampling, have informed us that prices vary very little to not at all within cities.[2] However, in a study of supermarket price setting, Levy, Dutta, Bergen, and Venable (1998) showed that large chains consist of pricing zones, or geographical groupings of stores, which can adjust prices based on localized factors. Large metropolitan areas can support several pricing zones. As we cannot guarantee that the prices do not vary within cities for the entire time series, we include the zip codes we used to draw our data to provide geographic areas for which we are confident that our data reflect the prices paid by consumers at these stores.[3] Following the terminology of Levy et al., we conduct our analysis at the pricing zone level.

[2]For example, early on in the data collection we gathered comprehensive prices for both chains from the wealthiest and poorest zip codes in Los Angeles for 4 weeks and found no differences.

[3]Conversations with professionals from both chains have revealed that prices match up in-store and online except in the case of inventory shortages. Moreover, the author conducted comparisons for a basket of 50 products in stores in Sacramento and Davis, CA for 2 weeks and found only one discrepancy between the prices in the stores and those reported online.

The dataset covers virtually all major supermarket departments, therefore including products that vary across many dimensions including size, storability, purchase frequency, price, and sales when applicable. Following HR (2004), we describe our data in terms of price series, consisting of prices throughout the time series for a given product, pricing zone, and chain combination.[4] All told we have just shy of 240,000 price series in our data, considering only those cases for which we have at least 50 weeks of price data over the 27-month time series. The entire dataset contains over 20 million observations, and the average price series contains 81 weekly observations. Table 2 describes the major supermarket departments.

For the majority of the data collection period, both chains engaged in HLP. The most common alternative to HLP is everyday low pricing (EDLP), defined by low, steady prices throughout the store with few to no sales. In the 1990s, Chain B rolled out an EDLP program in many of its stores, intended to equip the chain to better compete with Wal-Mart (Farris, Hayoung, Maitrejean, Schauer, & Seyffert, 2006). By the turn of the century, however, they abandoned the strategy in the face of falling profits. Chain A uses sales heavily in its pricing. In July of 2009, it announced it was rolling out EDLP in its northern California stores with the possibility of expansion into other divisions (Supermarket News, 2009). There has been no official word on this switch since that time, and the data on northern California stores still show heavy sales pricing activity.

Following HR (2004), we calculate annual modes for each price series and convert prices into scaled prices to measure price variability. That is,

$$\mathrm{p}_{j,t} = \frac{\mathrm{r}_{j,s,t}}{\mathrm{r}_{j,s,mode}}$$

where $r_{j,s,t}$ is the raw price, as reported by store s, of product j at week t and $r_{j,s,mode}$ is the modal raw price of product j at store s in the year containing week t.

Figure 1 shows how the price distribution, including sales, breaks down between the two chains. Aggregating over all departments, we see that both chains follow a similar price distribution. Prices are at the annual mode between 50 and 55% of the time, and then for each chain deviations from the mode are more likely to be price decreases. Table 3 takes the interchain comparison further, using several summary statistics pertaining to prices and sales. Shelf price is the regular price of products, not including sales. Sale price is the price when taking into account discounts, when applicable. Sale frequency is the percentage of time a product is on sale during the time series and sale depth is the average percentage difference between the shelf price and sale price during sales.

Due to the large sample size, all differences between chains are statistically significant. However, chains look quite similar throughout Table 3 in terms of sale frequency, depth, duration, and overall price variability. As demonstrated by Li (2010), there are at least four distinct pricing strategies that supermarkets in the United States can and do follow. It is thus vital to stress that our findings pertain only to HLP supermarkets, or HLP departments within stores, and not necessarily to food retailing as a whole.

3. COMPARISONS WITH HOSKEN AND REIFFEN (2004)

The dataset used by HR (2004) suffers from a number of drawbacks, as acknowledged by the authors themselves in many cases. Their data are monthly, while supermarket prices change on a weekly basis. We face no ambiguity with respect to the timing and depth of sales, as defined

[4] Both chains offer special sales for online shoppers that were typically based on meeting expenditure thresholds, but these were clearly distinguishable from normal sales obtainable through the use of club or loyalty cards, which are free for supermarket consumers. Such sales are ignored in this study.

TABLE 2. The Major Supermarket Departments

Department/abbreviation	Examples of products offered	Number of price series
Baby care (baby)	Baby food, formula, diapers, ointments and creams	3,462
Bakery (bakery)	Products baked on the premises, including cakes, donuts, bread, rolls	2,806
Baking and cooking (BC)	Cooking utensils, pots and pans, common baking ingredients such as flour and sugar	9,485
Boxed dinners and side dishes (BDSD)	Rice and pasta dishes, mashed potatoes, stuffing, macaroni and cheese	3,976
Beverages (Bev)	Soda, juice, bottled water, energy drinks	19,618
Candy (candy)	Packaged chocolates, fruit snacks, gum, mints	5,264
Cereal and breakfast foods (CBF)	Boxed cereal, oatmeal, breakfast bars, breakfast shakes	5,343
Canned goods (CG)	Canned fruits and vegetables, canned meats and seafood	9,061
Cleaning products (CP)	Sprays, aerosols, wipes, tools intended to aid in home cleaning	7,344
Condiments, sauces, and spreads (CSS)	Ketchup, mustard, hot sauce, hummus, chocolate syrup, honey	12,125
Coffee and tea (CT)	Coffee grounds, instant coffee, tea bags, tea leaves, coffee filters	6,745
Dairy (dairy)	Milk, butter, nonartisan cheese, sour cream, eggs	14,593
Dairy substitutes (DSub)	Soy, rice, and other alternatives to standard dairy products	686
Salad dressing and toppings (DST)	Salad dressing, vinaigrettes, bacon bits, croutons	4,645
Frozen food (FF)	Frozen meals, frozen fruits and vegetables, ice cream, frozen baked goods, juices	24,321
General merchandise (GM)	Products intended for the home or automobile	10,652
Health and beauty aids (HBA)	Medicine, vitamins, hygiene products, first aid, cosmetics	23,796
Mexican (Mex)	Taco shells and sauce, refried beans, salsa, guacamole mix, tortillas	4,972
Meat and seafood (MS)	Fresh or frozen meat and seafood products offered in the periphery of the supermarket	9,525
Packaged bread (PB)	Sandwich breads, packaged dinner rolls, hot dog and hamburger buns	6,021
Produce and floral (PF)	Fresh produce, flower arrangements, fresh herbs, vegetable platters	5,942
Pasta, rice, & beans (PRB)	Boxed or bagged pasta and rice, canned or dried beans	4,604
Pet care (pet)	Dog and cat food, pet carriers, flea and tick medication	6,021
Snacks (snack)	Cookies, crackers, snack bars, potato chips, beef jerky, salsa, dips	23,911
Soup and chili (SC)	Canned or freeze dried soups and chilis	6,962
Spices & seasonings (SS)	The spectrum of the spice rack, black pepper, salt, marinade mixes	5,822

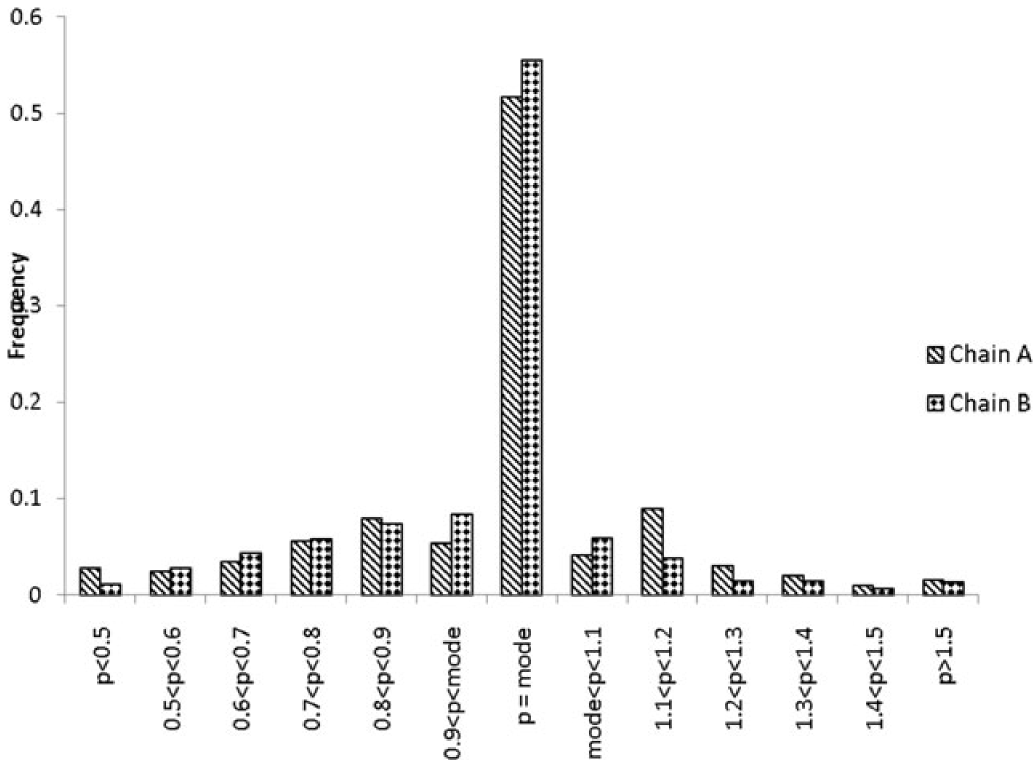

Figure 1 The Distribution of Scaled Prices for Chain A and Chain B.

TABLE 3. Comparing Chain A and Chain B Pricing Strategies, Mean (Standard Deviation)

	Chain A	Chain B
Number of observations	2,809,598	17,696,917
Proportion of prices above mode	0.13 (0.34)	0.19 (0.40)
Proportion of prices below mode	0.25 (0.43)	0.27 (0.44)
Sale frequency	39.49 (30.18)	42.63 (24.99)
Sale depth	23.83 (10.06)	23.42 (9.70)
Sale duration	5.41 (6.70)	5.10 (7.67)
Shelf price coefficient of variance	6.52 (7.26)	8.02 (5.69)
Sale price coefficient of variance	13.01 (7.38)	13.82 (7.32)

Note: Standard deviations in parentheses.

by the stores.[5,6] We are able to identify the chains at which prices and sales are observed and thus identify their respective pricing strategies. Hosken and Reiffen are unable to identify the names of the products sampled in their BLS data, only the general categories from which they are drawn. Probably the most important distinction lost due to this last point is that between

[5]For the purposes of the dataset and this analysis, individual products are defined entirely by their names. The data collection process stored complete product names for each chain, including brand name, size, and any descriptive attributes including flavor or nutritional variants (e.g. low salt, spicy). Product names occasionally change, however. Even in those cases for which we suspected that a name change had occurred for an identical product within a chain and pricing zone, we treated the names as two different products.

[6]However, as discussed at length below, the patterns observed with respect to sale duration indicate concerns with store-defined sales for use in the studies of retail sales.

TABLE 4. The Percentage of Prices Equal to, Above, and Below the Mode, Comparing Our Results to Hosken and Reiffen (2004) by Category

	Percentage of time at modal price			Percentage of prices* above mode*			Percentage of prices below mode		
	H&R	V&L** NB	V&L PL	H&R	V&L NB	V&L PL	H&R	V&L NB	V&L PL
Baby food	69.26	57.67	55.98	2.62	23.83	37.04	4.63	18.50	6.97
Bananas	56.03	74.63		14.06	14.38		26.20	10.99	
Canned soup	65.62	52.10	52.02	4.25	19.75	28.31	9.34	28.14	19.67
Cereal	63.12	47.46	60.54	2.87	22.08	23.11	6.72	30.45	16.35
Cheese	62.68	54.01	55.80	3.60	17.95	20.06	10.67	28.03	24.13
Cookies	70.71	48.85	57.39	3.24	16.95	21.44	10.75	34.12	21.17
Crackers	62.82	44.44	51.36	3.55	16.61	21.47	18.81	38.86	27.17
Eggs	39.89	55.87	50.95	15.47	23.13	27.33	17.82	21.00	21.71
Frozen dinners	65.31	54.76	83.89	4.44	17.72	12.57	13.60	27.50	3.54
Frozen OJ	55.89	69.29	51.25	7.87	7.09	25.87	18.10	23.61	22.87
Ground beef	60.66	62.22		4.51	13.18		14.91	24.60	
Hot dogs	62.65	51.22	49.05	3.59	12.80	22.74	15.22	35.98	28.21
Lettuce	27.57	56.77	55.03	26.19	15.90	13.75	31.43	27.32	31.21
Margarine	60.91	53.52	55.56	6.25	16.34	24.03	14.16	30.14	20.41
Peanut butter	61.62	57.71	60.91	4.20	14.67	16.12	10.60	27.61	22.96
Potato chips	71.43	51.23	47.98	3.60	19.03	34.69	12.73	29.73	17.33
Soda	60.35	49.10	56.71	7.46	21.51	30.25	18.77	29.39	13.04
White bread	68.33	56.75	53.45	3.71	10.87	12.66	9.46	32.38	33.88

*To facilitate the best possible comparison to Hosken and Reiffen (2004), we report only the prices that deviate at least 10% from the modal price in either direction. **Volpe and Li Authors of this study.

NB and PL products. A significant body of literature (Berges-Sennou, Bontems, & Requillart, 2004; Chintagunta, 2002; Connor & Peterson, 1992; Cotterill & Putsis, 2000) suggests that there is no reason to expect NBs and PLs to be priced according to the same patterns.

To facilitate the best possible comparison, we followed HR's approach to measuring price variability and the impact of sales. This entails assigning each individual price series annual modal prices and then scaling all raw prices according to the mode. Owing to the nature of HR's dataset, the authors were unable to observe sales and had to infer them. We conduct our analysis using both store-defined sales and sales as calculated by HR. For the purpose of this section, we limit our focus to only those product categories covered by HR. The organization of our data does not lend to easy examination of the nonfood categories of paper towels and soap; therefore, they are not included. The complete list of products included in each product category within our data is available from the authors upon request.

3.1. Deviations From the Modal Price

Table 4 shows the extent to which prices are at their annual modes and the shares of price deviations that are increases or decreases from the mode. In general, we find that the propensity of retail prices to remain at their annual modes was higher according to HR, i.e., HLP store prices exhibit more volatility in our data than do prices drawn from a variety of stores. Prices do not vary considerably between NBs and PLs in terms of general price stickiness. For potato chips and cookies the differences between results is the most striking. For those categories our time proportions at the mode are between 45 and 50 % lower than HR's.

Hosken and Reiffen stress the importance of distinguishing between perishable and storable products and it is interesting to note that the difference between results is reversed for perishable products. For eggs, bananas, ground beef, and lettuce we find prices to be at the mode more often than do HR. With the exception of beef, the differences are wide, ranging from 25 to 50%. A likely explanation of this difference is that the HR dataset incorporated stores that follow simple markup pricing for perishable products. Markup pricing is defined by steady markups applied to wholesale prices, and therefore features the strongest correlation between upstream and retail prices. Given that perishable, unprocessed foods typically exhibit more upstream price variation than do manufactured foods, the presence of markup stores in a retail dataset could significantly increase the observed price variability for these categories.

Overall, our findings are in agreement with HR's in that deviations from the modal price are more likely to be decreases rather than increases. In aggregate, HR found that 14.9% of all prices were at least 10% below the mode and 7.5% were at least 10% above the mode. Table 3 shows that we find these figures to be 25% and 13%, respectively, for Chain B and 27% and 19%, respectively for Chain A. Both differences are statistically significant at the 0.01. Hence, the overall difference in proportions around the mode is roughly equivalent between the two sets of findings. Though the impact of sales on price variation is explored in detail below, we find evidence that sales are the driving force behind the phenomenon that downward deviations from the mode are more common. Ignoring all sale prices but otherwise repeating HR's analysis, deviations upwards from the mode are significantly more common, overwhelmingly so in the case of PLs.

There are, however, some important differences to note at the categorical level. Although NB and PL products stay at their modal prices for roughly equivalent percentages of time, NB prices follow HR's results fairly well whereas PL prices do not. For 10 of the 16 categories for which we have PL data, increases from the mode are more frequent than decreases. This difference is significant at the 0.05 level for all cases save for cookies. In the next section, we show that the sale frequency of PL products is very high; in fact, the average PL product is on sale more often than it is not. The phenomenon of price increases outnumbering decreases occurs because for many PL cases the modal price is the sale price. Hence, deviations from the mode are most often returns to the unadvertised shelf prices for these products. We explore this phenomenon in detail below.

3.2. The Frequency, Duration, and Importance of Sales

The frequency of temporary sales and their impact on retail price variability were at the heart of HR's study. Several influential models on retail pricing (Sobel, 1984; Varian, 1980) are based on the use of temporary sales. Table 5 compares HR's findings with our own in terms of sale frequency and the percentage of total price variation explained by sales. To fully conduct this comparison, we rely upon two definitions of sales: the methodology used by HR as well as retailers' advertised sales. The former methodology entails including only those cases in which the price decreases by at least 10% and then returns to the original level after one period (one week in our data).[7] Additional results, considering other possible limitations, are available from the authors.

Table 5 illustrates clearly the importance of how sales are defined when conducting empirical research on retail pricing. The comparisons with HR's findings, and indeed the implications for the importance of sales in shaping price variability, vary considerably between the two methods of discerning sales. We begin with the use HR's methodology in comparing the results of the two studies. In this setting, our estimates of sale frequency for most categories are under 5%. These values are generally lower than the estimates obtained by HR, and in most cases are comparable in magnitude. However, these results come with a caveat that we revisit below, namely that using HR's method of sale identification discards the vast majority of the retailer-defined sales in the data set. Recall from Table 3 that the average promotional duration, for both chains, was over 5 weeks.

Table 5 also compares our "sale R^2" figures, or the percentage of price variation that can be attributed to sales, with those of HR. Also following HR, we calculate our sale R^2 values as the sum of all squared deviations from modal prices during sales as a percentage of all squared

[7]Readers are encouraged to refer to Hosken and Reiffen (2004) for a complete description of their methodology.

TABLE 5. The Frequency of Sales and Their Effect on Price Variation, Comparing our Results to Hosken and Reiffen (HR; 2004) by Category

	Using Sales as Defined by HR					
	Sale frequency			Sale R^2		
	HR	VL* NB	V&L PL	HR**	VL NB	VL PL
Baby food	1.16	2.47	2.02	22.00	2.99	0.39
Bananas	13.63	1.95		44.00	1.41	
Canned soup	3.48	2.44	2.13	30.00	7.45	2.77
Cereal	2.97	3.47	1.18	46.00	6.83	1.95
Cheese	4.51	2.64	0.93	28.00	5.76	1.24
Cookies	6.11	4.54	2.57	39.00	7.65	5.11
Crackers	9.79	4.88	2.45	42.00	8.29	5.13
Eggs	5.99	8.87	9.11	20.00	21.61	15.59
Frozen dinners	7.98	2.75	1.63	50.00	4.18	0.33
Frozen OJ	6.95	2.22	1.56	36.00	4.13	1.73
Ground beef	6.84	16.62		42.00	10.32	
Hot dogs	7.62	4.28	3.06	55.00	11.69	5.74
Lettuce	17.83	14.90	17.54	3.00	32.88	40.55
Margarine	5.62	2.74	2.68	30.00	7.17	4.32
Peanut butter	4.03	3.00	1.62	28.00	8.43	3.65
Potato chips	6.54	4.38	2.29	41.00	7.35	2.80
Soda	7.89	2.90	0.53	30.00	4.45	0.63
White bread	5.14	3.31	2.96	38.00	7.95	5.36
	Using sales as advertised by the retailers					
	Sale frequency			Sale R^2		
	HR	VL NB	VL PL	HR	VL NB	VL PL
Baby food	1.16	49.88	36.69	22.00	32.42	6.61
Bananas	13.63	59.17		44.00	14.41	
Canned soup	3.48	29.27	50.95	30.00	64.01	40.67
Cereal	2.97	48.70	50.68	46.00	64.81	40.37
Cheese	4.51	41.57	60.81	28.00	62.99	56.84
Cookies	6.11	45.85	52.29	39.00	63.64	63.11
Crackers	9.79	49.94	44.60	42.00	69.80	63.75
Eggs	5.99	21.93	52.32	20.00	41.36	41.81
Frozen dinners	7.98	70.37	81.02	50.00	69.18	7.26
Frozen OJ	6.95	56.29	61.28	36.00	68.83	53.47
Ground beef	6.84	31.91		42.00	54.77	
Hot dogs	7.62	34.10	31.44	55.00	84.33	60.53
Lettuce	17.83	22.76	45.46	3.00	62.08	67.12
Margarine	5.62	48.33	51.46	30.00	65.45	54.11
Peanut butter	4.03	29.98	34.70	28.00	64.03	46.95
Potato chips	6.54	43.00	46.50	41.00	58.84	39.09
Soda	7.89	49.30	54.29	30.00	59.18	30.85
White bread	5.14	27.27	54.17	38.00	59.39	69.88

*Volpe and Li. **HR (2004) provide a bar graph to represent these figures. We thank Daniel Hosken for providing the reported figures in a personal correspondence. Any errors are our own.

price deviations. The equation is

$$SaleR_{\mathrm{i}}^2 = \frac{\sum_{j,s,t}[(\mathrm{p}_{ijst}-1)^2|\mathrm{p}_{ijst}\text{being a promotional price}}{\sum_{j,s,t}(\mathrm{p}_{ijst}-1)^2} * 100$$

where *Sale* R_{i}^2 is the percentage of total price variation in category *i* attributed to sales and the remaining subscripts are unchanged from before. Also using HR's definition of sales, our sale

R^2 values are almost uniformly lower than those of HR. In several cases, the differences are considerable. For example, HR attribute 55% of hot dog price variation to sales, whereas our figures are 12% and 6% for NBs and PLs, respectively. Hosken and Reiffen generally attribute between 20 and 50% of all price variation to sales, across all categories.

The differences between our findings and those of HR are larger in magnitude and in the opposite direction when we rely upon sales as advertised by retailers. Hosken and Reiffen find that between 5 and 10% of all observations are temporary price discounts, whereas we find that NBs are on sale roughly 30 to 50% of the time and PLs are on sale 40 to 80% of the time. Our sale R^2 is higher than HR's for most categories and by a factor of about 100% for categories such as canned soup and margarine. However, the differences are generally closer to 50% and are not as striking as we might expect, given the vast differences in sale frequency between HR's data and our own. This is especially true when considering that PL sale frequency is almost uniformly higher than for NBs, yet PL sale R^2 is almost uniformly lower. Also, our comparison with HR in terms of time spent at the modal price summarized in Table 4 is more surprising when considering the differences in sale frequency. Despite observed sale frequency that is in some cases 4 or 5 times greater than that measured by HR, prices deviate from the mode only 25 to 50% more often.

A purported advantage of our own dataset is the lack of ambiguity pertaining to sales, meaning that we need not perform any statistical analysis to identify the frequency and timing of sales. Nevertheless, we introduce a caveat to the strict use of advertised sales that is important to both consumers and researchers, namely that temporary price discounts and advertised sales need not necessarily be the same in today's supermarket industry. Limiting our focus to those categories featured in the HR study, we find six products to be on sale for all 122 weeks of the dataset. We observe thousands of sales lasting longer than 50 weeks. Certainly, these phenomena cannot properly be classified as temporary price discounts. Figure 2 demonstrates that less than one quarter of all sales in the data last only 1 week.

One of the principle objectives of HR was to test observed retail price variation against the implications of influential models of pricing, particularly those of Varian (1980) and Sobel (1984). The Varian model implied that prices should change every period, or at least very frequently, as retailers employ sales to discriminate between informed and uninformed consumers. The Sobel model posited that, at equilibrium, prices should be high most of the time, but lowered periodically to capture the demand of consumers with low reservation prices. Therefore, both models predict sales of short duration, likely one time period. However, the high frequency of multiweek sales, even discounting those that last 6 weeks or longer, indicates that supermarket managers are pursuing objectives other than consumer purchase acceleration or simple price discrimination. The marketing literature is rich with additional and alternative motivations for offering sales, including store traffic (Blattberg et al., 1995), full-price complementary purchases (Mulhern & Padgett, 1995), and category demand expansion through increased consumption rates (Bell, Iyer, & Padmanabhan, 2002). Each of these objectives are consistent with multiweek sales and suggest that including only those sales lasting 1 week may hinder our full understanding of the importance of sales in the retail price landscape.

The obvious question thus arises: How long can sales last until they can no longer be considered temporary? Seeking an answer can help to reconcile our findings with those of HR and provide meaningful guidance to future researchers working with sales in retail price data. On one hand, relying on HR's definition of sales discards over 75% of the advertised sales in our dataset. However on the other hand, accepting retailers' advertisements as the correct definition of sales results in intervals of rigidity lasting 50 weeks or longer being classified as sales. This practice runs contrary to every model of sales and pricing of which we are aware.

The literature is of little help in distinguishing between temporary price discounts and long-term price changes, advertised as sales. For example, Pesendorfer (2002) noted the incidence of multiweek sales in his retail dataset but removed them due to their lack of theoretical support. Bils and Klenow (2004) provide a starting point by showing that prices for over 300 categories of goods change an average of approximately every 4 months. Hence, we argue that any sale

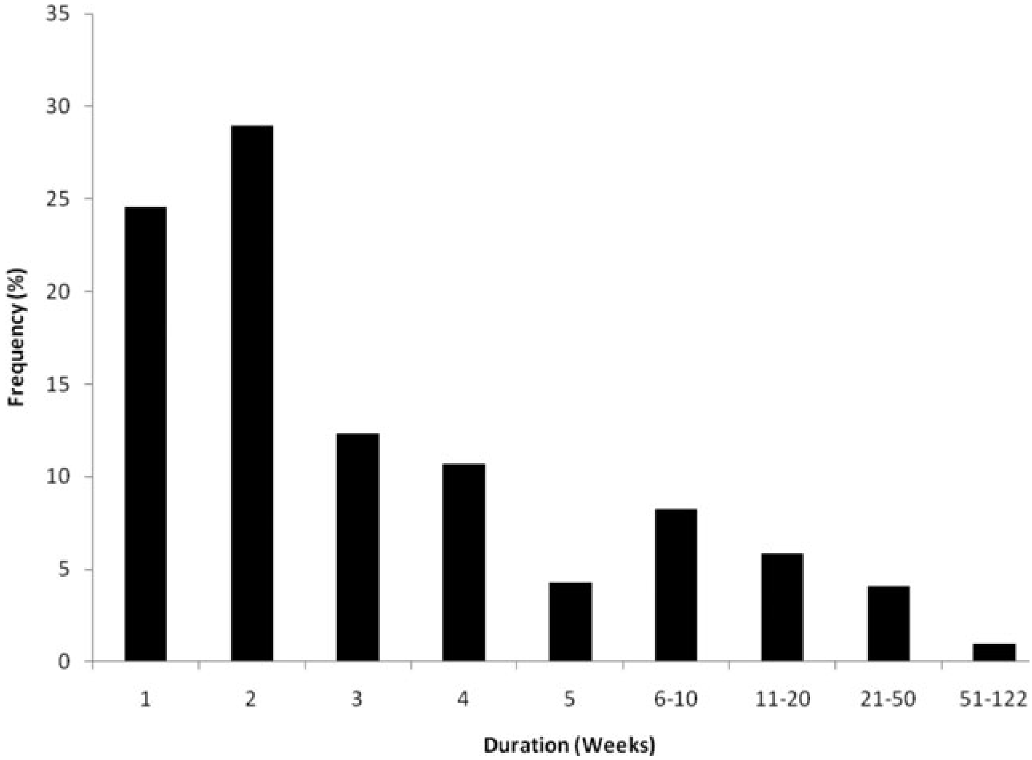

Figure 2 Sale Duration, by Week, for All Products.

lasting longer than 4 months, or 16 weeks in our data, is not a temporary price reduction. Hosken and Reiffen argue that using monthly data does not bias their findings despite the fact that supermarket prices change weekly. This is a point we examine more fully in this study, and accordingly we consider 4 weeks to be a possible delineation point between temporary and more permanent price changes. Table 6 revisits our findings with respect to the frequency and impact of sales, considering 4 and 16 weeks as the maximum sale durations.

The duration of a temporary price discount, or sale, is highly influential on the results. For both PL and NB products, the sale frequency and R^2 fall if we place limits on the maximum sale duration. The differences are larger among PL categories, as PLs feature longer sales on average than do NBs. Importantly, our numbers grow closer to HR's, but for the most part still exceed them. Sale frequency generally runs between 15 and 40% whereas sale R^2 remains between 30 and 60%. For certain categories, such as baby food and frozen dinners, we now attribute less total price variation to sales than does HR. However, for other categories, such as margarine, canned soup, and hot dogs, our estimates of sale R^2 are between 20 and 30 percentage points greater.

3.3. Monthly Versus Weekly Data

The monthly frequency of the dataset used by HR is acknowledged to be less than ideal by the authors due to the fact that retail food prices typically change on a weekly basis. However, the authors argue that this ought not to bias the key results. As a simple test of this assertion, we apportion our dataset, once again restricting our view to those categories examined by HR, according to the weeks of the month. This yields four datasets, each representing the 27 months of our dataset using only the first, second, third, or fourth weeks. We then apply

TABLE 6. Sale Frequency and R^2 for Maximum Sale Lengths of 4 and 16 Weeks

	Maximum sale duration: 4 weeks				Maximum sale duration: 16 weeks			
	Frequency		Sale R^2		Frequency		Sale R^2	
Category	PL	NB	PL	NB	PL	NB	PL	NB
Baby food	20.96	17.13	5.93	20.45	36.35	37.24	64.52	28.58
Bananas		2.45		9.92		5.31		12.58
Canned soup	21.71	16.95	27.16	51.34	41.05	24.37	37.43	60.41
Cereal	15.15	24.11	25.25	47.81	33.50	40.42	33.14	59.68
Cheese	13.43	18.34	19.06	39.99	34.45	29.65	34.41	52.21
Cookies	24.79	31.52	49.85	53.62	42.97	40.70	60.92	61.77
Crackers	23.94	33.87	49.56	55.78	37.63	45.81	61.19	67.14
Eggs	11.27	18.44	18.30	38.64	31.11	21.19	31.92	41.09
Froz. Dinners	11.36	19.09	2.47	28.66	33.12	44.63	2.54	53.94
Frozen OJ	17.75	15.40	20.33	29.99	46.09	39.63	40.85	49.56
Ground beef		20.29		44.53		29.18		52.75
Hot dogs	28.21	29.68	53.95	79.51	31.31	33.33	60.32	83.76
Lettuce	21.83	16.54	55.92	56.96	31.89	21.32	64.50	61.68
Margarine	25.53	19.03	38.92	51.59	36.41	32.00	46.22	59.92
Peanut butter	18.19	20.77	38.70	59.33	26.94	26.21	45.40	63.42
Potato chips	22.90	30.43	26.58	49.96	35.14	39.58	28.46	56.41
Soda	10.60	20.11	12.39	31.62	26.50	35.77	20.00	48.54
White bread	27.52	22.98	50.96	53.92	41.30	26.11	61.90	58.83

Note: PL = private label; NB = national brand.

TABLE 7. Price Dispersion and Summary Statistics by Week

Week	Num.	%observations at mode	%observations above mode	%observations below mode	Mean sale frequency	Mean sale depth
1	538710	51.21	19.69	30.13	42.20	26.00
2	534179	51.21	20.93	29.21	42.22	25.99
3	503141	51.26	18.21	29.76	42.16	25.99
4	488497	51.18	17.87	29.86	42.22	25.97
Week	Shelf price coefficient of variance	Sale price coefficient of variance	Mean scaled shelf price	Mean scaled sale price	Mean sale R^2	Mean sale duration
1	0.07	0.15	1.01	0.98	62.34	4.74
2	0.07	0.15	1.01	0.98	62.33	5.19
3	0.07	0.15	1.00	0.97	62.48	4.21
4	0.07	0.15	1.00	0.97	62.33	3.94

HR's methodology to each dataset individually and calculate additional summary statistics to essentially mirror the information contained in Table 3. For clarity of presentation, we aggregate our findings and report only statistics for NB products. The results are summarized in Table 7.

As Table 7 shows, the findings are very similar across weeks. In many cases, the differences across weeks are in the tenths or even hundredths of a percentage point. Moreover, keeping in mind that these results are aggregated across chains, the weekly statistics are firmly in line with those in Table 3. The figures for percentage of observations at the mode, the distribution between increases and decreases, sale frequency, and depth are all virtually unchanged by the use of monthly data. The only figure that varies noticeably across weeks is sale duration, which we measure in weeks and was not studied in HR's work. No differences across weeks are statistically significant. Our findings in this respect are a testament to the robustness of HR's methods and should be encouraging to researchers limited to the use of monthly data.

4. EXAMINING ALL SUPERMARKET DEPARTMENTS

In this section, we extend the analysis beyond the categories examined by HR. Another major strength of our dataset is the scope of product coverage. We now take full advantage of this scope to check to see if the major generalizations gleaned from the previous section can be applied to the HLP supermarket as a whole. We calculate sale frequency and sale R^2 using 16 weeks as the maximum length of a temporary sale. Table 8 presents our storewide findings, by department and distinguishing between NBs and PLs. Recall that the full department names and descriptions are available in Table 2.

With very few exceptions, the average product is at its modal price at least 50% of the time. Among NBs, which constitute the majority of products, our figures are approximately 10 to 15 percentage points below those of HR (2004). We find that prices are particularly rigid for those departments featuring the least sale activity, such as bakery and produce. PL prices almost uniformly spend more time at the annual modes, which we attribute to the extended duration of PL sales. For eight of the departments, the average PL sale duration is longer than 10 weeks. We maintain that HR's lower estimates of price variation reflect the aggregation of supermarkets using different pricing strategies. HLP stores, which constitute the majority of U.S. supermarkets, exhibit greater price variability than do stores of other formats.

Storewide, deviations from modal prices are more likely to be decreases rather than increases. Due to the large sample size, all differences between upward and downward proportions are significant at the 0.01 level. Among the 28 major NB departments, decreases are more likely for all departments save for baby care, which is a unique supermarket department in many respects. This pattern is clearer looking at the entire store than at the category level, where we observed several instances of more frequent price decreases. The pattern is less clear for PLs, for which 15 of the 26 departments show more frequent price increases. As before, we attribute this to the fact that the average PL is on sale more often than it is not. Our findings confirm the notion that HLP supermarkets' pricing strategy treats NBs and PLs differently. To our knowledge, no existing pricing theory directly explains why PLs might be advertised as being on sale for consistently long durations of time.

Sale depth is the most consistent facet to retail pricing patterns. Nearly all departments, NB and PL, show an average sale depth between 20 and 25%. The few exceptions to this include NB pet care products, which like baby care is somewhat distinct from the remainder of the supermarket, and departments featuring very low sale activity, such as meats and produce. Therefore, our findings with respect to depth are very consistent across all packaged and processed goods. This leads us to consider that HLP supermarkets manage their sale pricing strategies in terms of the products selected and the frequency with which sales are implemented, but less so in terms of depth.

The duration of sales, which is rarely discussed in the literature on pricing, provides motivation for interesting future research. The majority of sales are short, as 53% of all sales are 1 or 2 weeks long (see Figure 2). However, 1 in 5 sales is longer than 5 weeks, and 1 in 10 is longer than 12 weeks. Returning to Table 8, PL sales are generally longer. Departments with relatively long sales include beverages, dairy, dairy substitutes, and frozen foods. As discussed previously, such lengthy sales do not conform to certain well-known models of retail pricing. However, they may be consistent with sales as tool by which retailers achieve other objectives. In addition to those described above, multiweek sales may also be consistent with the incentive on the part of retailers to sell large quantities of specific items due to manufacturer scan back deals or trade allowances. By these mechanisms, upstream manufacturers reimburse retailers directly based on quantities sold during specified periods (Rao, 2009).

Our estimates of sale frequency, even limiting the maximum duration of sales to 16 weeks, remain well above HR's estimates. Excluding those sales that cannot be considered temporary, sale frequency is generally higher for NBs. Estimates across departments range from roughly 25 to 50%. Frequency is the highest for frozen foods, beverages, and breakfast foods; it is the lowest for produce and baked products, both fresh and packaged. The departmental estimates of sale R^2 are also well above those of HR as well as our own measurements for the product categories

TABLE 8. Price Variation and Summary Statistics for All Supermarket Departments

	Num. of Obs.		% Obs. at mode		% Obs. above mode		% Obs. below mode	
Department	NB	PL	NB	PL	NB	PL	NB	PL
Baby	211,661	19,449	59.97	56.07	22.69	36.04	17.34	7.89
Bakery	226,579	15,917	76.15	74.20	9.62	9.05	14.24	16.74
BC	707,876	98,472	52.84	59.08	17.48	17.86	29.69	23.06
BDSD	313,913	33,424	48.53	65.00	21.97	22.59	29.50	12.42
Bev	1,480,311	253,517	52.49	61.59	20.05	23.52	27.46	14.89
Candy	434,106	11,223	50.35	60.96	17.17	17.68	32.49	21.37
CBF	403,868	73,311	47.96	58.39	21.57	23.42	30.47	18.20
CG	611,442	166,231	50.97	63.07	18.61	20.91	30.42	16.01
CP	546,474	83,004	52.19	60.00	17.58	21.69	30.23	18.31
CSS	884,696	171,822	51.98	57.78	18.11	21.54	29.91	20.69
CT	481,725	99,098	51.27	61.44	20.46	15.93	28.27	22.63
Dairy	882,820	461,391	53.55	58.84	17.79	20.27	28.66	20.89
DST	347,665	65,432	50.48	63.86	16.57	18.66	32.95	17.49
DSub	51,736	9,938	57.09	56.13	16.65	25.34	26.26	18.54
FF	1,574,319	518,935	51.61	62.44	19.76	22.15	28.63	15.42
GM	688,707	191,722	56.25	58.57	18.81	22.51	24.95	18.91
HBA	1,483,407	280,956	54.30	64.53	21.30	18.84	24.40	16.64
Kosher	44,152		52.88		20.48		26.64	
Mexican	355,525	38,406	61.33	61.57	13.63	20.51	25.04	17.93
MS	799,077	40,441	55.17	60.24	15.21	14.45	29.61	25.31
MSub	38,839	3,057	54.80	72.20	16.48	19.50	28.72	8.31
PB	374,576	87,892	61.47	56.33	11.03	13.51	27.50	30.17
Pet	529,827		57.21		18.23		24.56	
PF	496,490	48,785	60.96	62.49	16.28	14.33	22.76	23.19
PRB	289,241	112,636	50.65	59.49	18.93	19.97	30.42	20.54
SC	551,083	73,073	51.48	53.44	20.32	27.23	28.20	19.33
Snack	1,794,317	242,971	50.18	57.54	19.10	19.80	30.72	22.66
SS	421,258	62,303	53.06	51.03	17.65	20.94	29.30	28.03

	Sale R^2		Mean sale freq		Mean sale depth		Mean sale duration	
Department	NB	PL	NB	PL	NB	PL	NB	PL
Baby	31.14	6.78	38.70	25.84	20.02	20.28	7.18	5.75
Bakery	47.52	69.43	9.85	10.85	24.18	17.75	2.30	1.82
BC	58.67	45.35	25.09	25.26	25.57	19.50	3.69	6.04
BDSD	58.27	27.93	39.35	35.76	26.10	23.91	4.74	10.06
Bev	55.37	35.91	42.42	38.27	26.46	23.49	6.13	11.93
Candy	58.20	44.35	30.10	29.56	28.31	30.88	4.06	7.33
CBF	59.65	42.54	40.15	34.62	24.13	22.08	4.95	9.53
CG	53.96	31.82	29.47	28.61	23.05	23.66	4.60	8.29
CP	53.74	34.62	36.35	40.10	21.49	21.18	4.60	10.54
CSS	55.13	39.59	26.71	31.62	19.84	20.62	4.09	7.78
CT	54.44	46.51	31.12	28.14	23.72	22.99	4.16	6.06
Dairy	56.44	44.22	41.20	42.20	19.86	20.85	7.26	14.63
DST	64.28	41.93	31.51	40.44	28.01	23.92	3.73	12.45
DSub	55.75	45.66	23.44	41.82	21.05	18.20	5.13	26.36
FF	61.56	44.21	52.75	47.00	23.21	25.56	7.61	16.44
GM	47.72	37.94	30.84	34.13	22.75	22.38	6.18	11.01
HBA	47.85	34.19	33.75	31.24	22.66	19.94	4.32	7.67
Kosher	44.87		20.11		25.66		5.51	
Mexican	55.85	35.75	24.78	35.90	19.43	20.25	4.42	7.51
MS	60.88	49.08	28.95	15.72	23.66	13.66	2.58	1.70
MSub	69.51	22.43	25.01	41.36	24.39	27.08	3.88	9.51

TABLE 8. Continued.

	Sale R^2		Mean sale freq		Mean sale depth		Mean sale duration	
Department	NB	PL	NB	PL	NB	PL	NB	PL
PB	61.15	61.98	18.97	30.37	26.91	26.88	2.58	3.37
Pet	47.95		35.71		16.51		5.11	
PF	41.49	50.22	18.12	28.73	30.21	25.75	3.11	5.21
PRB	50.04	44.96	32.93	31.93	22.06	19.64	4.75	8.32
SC	59.33	37.57	25.08	36.68	28.53	21.64	4.29	8.34
Snack	57.81	51.86	37.45	34.00	25.63	20.99	3.97	5.79
SS	56.60	50.71	27.82	29.15	21.31	20.85	4.87	5.96

Note: All statistics are calculated with sales, as defined by temporary price reductions, having a maximum duration of 16 weeks. PL = private label; NB = national brand.

of the above section. For most NB and many PL departments, sales are very influential in determining price variation, explaining 50 to 60% of all price changes. Hosken and Reiffen's observation that relatively few sales can have major impacts on price variation holds true, as sale R^2 remains high even for many departments with relatively few sales, such as baking and cooking and meats.

We recognize that 16 weeks constitute a longer sale duration than most economic models predict, assume, or allow. Furthermore, the retailer's motivations behind a price reduction lasting 16 weeks may well differ from those behind considerably shorter durations. We choose this duration in an effort to strike a balance between allowing multiweek sales while ignoring longer-term changes in price. Setting the maximum sale duration at this length, as demonstrated in the previous section, brings about noticeable changes in the estimated impacts of sales of price variability as well as our general understanding of sales. The proper theoretical support and an econometric analysis required to understand why retailers engage in such lengthy sales and how they decide where to apply them is left for future work.

5. CONCLUSIONS

This study is rich with findings on HLP supermarket pricing and it is our hope that it will provide a valuable resource and stimulate work for researchers in food retail economics. Using a unique dataset with the scope of nearly the entire supermarket, our main findings are summarized as follows:

1. We find that prices remain fixed at their annual modes to a smaller extent than did Hosken and Reiffen (2004). Additionally, we find that the frequency of sales and the importance of sales in explaining retail price variation are both higher than their estimates. On average, products are on sale between 25 and 50% of the time and these sales consistently explain 50 to 60% of all price variation. We attribute the differences between the findings of the two studies in part to the fact that HR aggregated across multiple supermarket chains without being able to identify pricing strategies.
2. The empirical definition of a sale or temporary price discount, is critical to determining the role of sales in the retail landscape. By measuring sales as single-period reductions in price, our estimates of the incidence of sales and their effects on price variation are generally smaller than are those of Hosken and Reiffen. However, less than one quarter of the sales we observe, as defined by the stores, last for only 1 week. Nearly half last for longer than 2 weeks. By limiting the duration of sales using guidelines from the literature, but allowing

them to last longer than 1 week, we obtain estimates of the impact of sales that exceed those of Hosken and Reiffen.

3. For HLP stores, deviations from the modal price are more likely to be downward. However, this is only true for NBs, as PL deviations from the mode are more likely to be increases than decreases. Given that NBs outnumber PLs, decreases dominate on a storewide basis. We attribute this effect almost entirely to sales, as excluding sales produces the opposite result.
4. In general, important differences persist between NB and PL prices. Private label prices are more rigid and exhibit much longer store-defined sales. Thus, the definition of a sale, particularly with respect to duration, has a greater impact on the perceived impacts of sales on PL prices than more NB prices. It may not be appropriate for researchers to pool NB and PL prices and treat them identically when conducting empirical work at the retail level.
5. Sale duration can be very long, approaching permanence, if one accepts that all prices advertised as sale prices are legitimate sales. Researchers need to take care in treating very long sales as temporary price discounts in empirical work. Our results change substantially, in terms of measuring the frequency and impact of sales, if we treat sales of great duration as long-term price changes.

In terms of future research, a similar investigation into the pricing patterns and variation of supermarkets using alternate pricing schemes is motivated. This is particularly true for EDLP stores such as Wal-Mart. The literature lacks a theoretical explanation of the prevalence of long-term sales or supermarkets' motivation for applying them. It would also be useful to reach an understanding as to how to properly distinguish between temporary discounts and long-term price changes among those prices labeled as sales.

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