Price Differentials Across Outlets in Consumer Price Index Data, 2002-2006

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September 2007

The authors thank Aylin Kumcu for valuable research assistance and participants in the Division of Price and Index Number Research seminar series for helpful comments and suggestions. All views expressed in this paper are those of the authors and do not necessarily reflect the views or policies of the U.S. Bureau of Labor Statistics.

I. Introduction

In this paper we provide new evidence on the impact on the U.S. Consumer Price Index (CPI) of the appearance and growth of new types of product outlets. For decades, analysts both within and outside the Bureau of Labor Statistics (BLS), the agency that produces the CPI, have known that consumers can benefit when new stores and delivery channels offer lower prices. Examples of these new outlets include chain store supermarkets, supercenters, warehouse clubs, and the internet, and many of the associated trends in consumer shopping patterns are still continuing.

Unfortunately, obstacles both conceptual and operational have precluded statistical agencies like the BLS from fully incorporating those benefits into price indexes. Some of these same factors have made it difficult for researchers to estimate the resulting potential index bias. The most recent analysis using BLS data, which has informed almost all expert estimates of overall CPI bias, is based on the period 1987-1989.

The research we present here uses regression analysis to compare food prices across CPI outlets during the years 2002 through 2006. In addition to providing estimates for a more recent time period, we are able to go beyond previous work in several ways by using the CPI Research Database developed by BLS. Most notably, we have detailed information on outlet type, as well as on the detailed characteristics of individual items priced in the CPI. Although we make no attempt in this paper to compare the quality of outlets and outlet categories, ours is the first research to adjust for differences across outlets in the specific characteristics of items sold.

Over the time period we study CPI food samples exhibit a steadily increasing share of prices from discount department stores and from warehouse and club stores. This is consistent with the national trends reported for the grocery industry as a whole. Despite these trends, however, large grocery stores remain the predominant outlet type in our sample. Consistent with our expectations, we also observe in the CPI data that different outlet types charge substantially different average prices. The lowest average prices are often found in warehouse/club stores, and large grocery stores often have the highest average prices. Interestingly, within many item categories, sale prices by large grocery stores are approximately the same as the regular prices charged by discount department stores and warehouse/club stores. That result suggests that in choosing whether to shop at large grocery stores, consumers evaluate the tradeoff between higher overall outlet quality and the relative inconvenience of only occasional sales.

We also are able to adjust for numerous differences in item characteristics, which exist even within the relatively homogeneous item categories that we, following previous authors, focus on. Package size and organic certification are examples of these measures of item quality. Once item quality is accounted for, we find that the prices at discount department stores are closer to those at large grocery stores for 11 of our 14 item categories. Sale prices at large grocery stores also move closer to the non-sale prices in 11 of 14 items when item quality is held constant. Those results argue that items at discount department stores and those offered at sale prices in large grocery stores are of lower quality. However, adjusting for item quality reduces the gap between prices at warehouse/club stores and large grocery store prices in only six of 14 items. Finally, we simulate the impact of changing shopping patterns on average prices in our CPI samples.

We find that the changing mix of outlet type between 2002 and 2006 had a significantly negative impact on average prices (in a statistical sense) for eight of the 14 items.

II. New Outlet Bias

Analysts have long recognized the potential problems caused for a Consumer Price Index by the appearance of new outlets. Feasible solutions for those problems have been difficult to identify, however.

It is important at the outset to distinguish the problem of new outlets from the substitution bias that can arise when there is a change in the relative prices charged at different outlets. For example, in response to an increase in sales or excise taxes in one local jurisdiction, consumers may shift their purchases of gasoline or apparel to outlets in an adjoining area. In this situation, changes in a CPI exceed changes in a cost-of-living index (COLI) unless (1) the CPI is based on a representative sample of outlets in different jurisdictions, and (2) the CPI employs an index formula that allows for consumer response to relative price change. This substitution bias is addressed in the U.S. CPI through its probability sampling and continuous rotation of outlets—albeit with a lag—and by its use of a geometric mean formula, which will approximate a COLI if consumers exhibit a roughly unitary elasticity of substitution across outlets.

As noted in the recent *Consumer Price Index Manual* published by the International Labour Organization,[1] the bias from new outlets is conceptually identical to the well-known problem of new product bias. The introduction of a replacement model of computer with improved speed and storage capability is equivalent to the introduction of a remodeled grocery store with better lighting and faster checkout handling. The appearance of a wholly new product type, such as a mobile telephone that can take photographs, is conceptually equivalent to the appearance of a new outlet type, such as an Internet site that offers DVD rentals. In some cases the new good and new outlet are combined, as in the example given in the Boskin Commission report on the CPI of Tuscan and Thai restaurants that brought to American consumers a wider variety of ethnic food specialties.[2]

The concern of this paper, however, is with the appearance of new outlets that offer lower prices for products that are essentially identical to those available at existing stores. That issue has been the focus of most prior discussions, and empirical analyses, of outlet bias as well. In general, statistical agencies do not construct basic CPI indexes using unit values. First, samples of items and outlets are selected, and then the item prices are collected on a monthly or other recurring basis within the sample of outlets. The index is computed as an average (the exact form of which depends on formula and weighting) of the changes over time for the sampled item-outlet pairs. Those changes are measured as ratios of prices, and longer run changes are estimated by multiplying those ratios together.

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[1] International Labour Office (2004), p. 213.
[2] U.S. Senate, Committee on Finance (1996), p. 24.

For example, elementary item/area indexes for food in the CPI employ a geometric mean formula. The log change in the index between times 1 and 2 for a sample of outlets i=1,…, N is given by

$$\ln\left(\frac{I_2}{I_1}\right) = \sum_i w_i \ln\left(\frac{P_{i,2}}{P_{i,1}}\right) \tag{1}$$

where we assume for simplicity that only one item is priced in each outlet and we abstract from some computational details in the calculation of the sampling share weights w_i attached to the different outlets.

The log change in the index between times 1 and 3 is given by

$$\ln\left(\frac{I_3}{I_1}\right) = \sum_i w_i \ln\left(\frac{P_{i,2}}{P_{i,1}}\right) + \sum_i w_i \ln\left(\frac{P_{i,3}}{P_{i,2}}\right) \tag{1a}$$

Rearranging,

$$\ln\left(\frac{I_3}{I_1}\right) = \sum_i w_i \ln\left(P_{i,3}\right) - \sum_i w_i \ln\left(P_{i,1}\right) \tag{1b}$$

Thus, the log change in the index is the difference between the weighted averages of log prices in periods 3 and 1.

Now let time 2 be an “overlap” period in which a new outlet sample j=1,…,M is introduced. This new outlet sample will be accompanied by new sampling share weights v_j that reflect purchasing patterns in a more recent period than do the weights for the units in the outgoing sample. Then the change in the index between times 2 and 3 is defined by

$$\ln\left(\frac{I_3}{I_2}\right) = \sum_j v_j \ln\left(\frac{P_{j,3}}{P_{j,2}}\right) \tag{2}$$

In this case, the log change in the index between times 1 and 3 is found by combining (1) and (2),

$$\ln\left(\frac{I_3}{I_1}\right) = \left[\sum_i w_i \ln\left(\frac{P_{i,2}}{P_{i,1}}\right)\right] + \left[\sum_j v_j \ln\left(\frac{P_{j,3}}{P_{j,2}}\right)\right] \tag{3}$$

and rearranging

$$\ln\left(\frac{I_3}{I_1}\right) = \left[\sum_j v_j \ln\left(P_{j,3}\right) - \sum_i w_i \ln\left(P_{i,1}\right)\right] - \left[\sum_j v_j \ln\left(P_{j,2}\right) - \sum_i w_i \ln\left(P_{i,2}\right)\right] \tag{4}$$

Equation (4) shows that the change in log index level can be written as the difference between the log-mean price in period 3 in the new sample and the log-mean price in period 1 in the old sample, *less* the difference in average prices charged by the two sets of outlets in time 2. Only if those two contemporaneous sample average prices are the same will the two-period CPI index change be the difference in weighted averages, as in (1b).

The focus of this paper, and most discussions of new outlets bias, is on the effects of trends in the market shares of outlet categories such as warehouse clubs or discount department stores. To characterize these effects, we assume that each sample outlet falls into one of a set of outlet categories k=1,…,S. We define the share weight of category k as the sum of the weights of the outlets in that category, i.e., $W_k = \Sigma\, w_i$ and $V_k = \Sigma\, v_j$ for all outlets i and j in category k. In order to avoid nuisance terms, we make the further simplifying assumption that the log mean prices in time t for category k are the same in the old and new samples; that is, that

$$\ln\left(\overline{P}_{k,t}\right) = \left[\left(\frac{1}{W_k}\right)\sum_{i\in k} w_i \ln\left(P_{i,t}\right)\right] = \left[\left[\left(\frac{1}{V_k}\right)\sum_{j\in k} v_i \ln\left(P_{j,t}\right)\right]\right]$$

Under these assumptions we can rewrite equation (3) as

$$\ln\left(\frac{I_3}{I_1}\right) = \left[\sum_k W_k \ln\left(\frac{\overline{P}_{k,2}}{\overline{P}_{k,1}}\right)\right] + \left[\sum_k V_k \ln\left(\frac{\overline{P}_{k,3}}{\overline{P}_{k,2}}\right)\right] \tag{5}$$

which we can rearrange to obtain

$$\ln\left(\frac{I_3}{I_1}\right) = \left[\sum_k V_k \ln\left(\overline{P}_{k,3}\right) - \sum_k W_k \ln\left(\overline{P}_{k,1}\right)\right] - \left[\sum_k (V_k - W_k) \ln\left(\overline{P}_{k,2}\right)\right] \tag{6}$$

The first bracketed term in (6) is the difference between the weighted averages of log prices in times 3 and 1, and the second term is the product of the category log prices in period 2 and the changes in shares of those categories. If, for example, lower priced store categories have a larger weight in the new sample, that effect will implicitly be subtracted from the simple unit-value change in the calculation of the CPI. Whether one views this as appropriate depends on one’s belief about differences in quality-adjusted prices across categories. If consumers view outlets as equivalent except for the prices those outlets charge, then the first term in (6) would provide a better approximation than the CPI index to changes in the cost of living. Conversely, if prices in different outlet categories are equal on a quality-adjusted basis, then incorporating the second term in (6) is essential in order to avoid index bias.

The recent Committee on National Statistics report *At What Price*[3] provides a clear and careful discussion of the specific issues raised by the handling of new outlets in the U.S. CPI. Within each item and area category in the CPI, the BLS develops an outlet sampling frame using the Telephone Point-of-Purchase Survey, or TPOPS. Outlets are sampled from the TPOPS frame in proportion to their estimated sales within the item category. Then, BLS staff select individual items for pricing within the store, again using a probability-proportional-to-size procedure.[4] This process ensures that the CPI sample will include a wide range of specific items in each category. At the same time, it makes it unlikely that new and continuing outlets will be represented by identical items, even when their distributions of products sold are similar. This complicates the analysis of

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[3] National Research Council (2002), pp. 167-177.
[4] For details on this and other aspects of CPI procedures see Bureau of Labor Statistics (2007).

potential outlet bias and would likely also complicate the implementation of any solutions.

The implicit assumption used in the CPI is that any cross-sectional differences in the prices charged in different outlets for the same item are attributable to outlet-related variation in "quality": stores offering lower prices may be less conveniently located, have inferior customer service, offer more limited product selection, require large volume purchases, and so on. Intuitively, in a static equilibrium in which outlets offer different prices there must be exactly offsetting differences in quality. If not, one outlet would increase its share of the market.

The CPI assumption of equal quality-adjusted prices across outlets is not just consistent with the equilibrium assumptions used in numerous economic analyses, it is convenient to implement. It is called into question, however, by observable trends in consumer shopping patterns such as the growth in chain-store supermarkets in the 1950s and 1960s. More recently, the ongoing increase in the market shares of supercenters and warehouse club stores has been a prominent feature of many product markets.[5] One explanation for this increase would be that, even after quality adjustment, prices at those stores are lower than at more traditional stores.

In this paper we do not attempt to reach definitive conclusions about quality-adjusted price differentials. Examination of store-related quality characteristics and estimation of their value to consumers have to be left for future research. Our focus here is on whether, in CPI data, prices are systematically lower at some types of outlets than at others. In estimating the size and statistical significance of these differences we are able to adjust for detailed characteristics of the items sold at sample outlets rather than assuming that all products within an item category are essentially equivalent.

III. Previous Empirical Research on CPI New Outlet Bias

As far back as the 1960s, the BLS carried out an empirical examination of potential bias in the CPI from the appearance of new outlet types. Ethel Hoover and Margaret Stotz (1964) cited Census data showing that the percentage of U.S. food sales accounted for by chain stores rose from 34 percent to 44 percent between 1948 and 1958. The BLS introduced those 1948 weights into the CPI at the end of 1955 and the 1958 weights late in 1961, with several interim adjustments during the intervening years. In each case, however, the new weights were introduced in such a way as to eliminate any impact on the index level of the difference between the mean price levels in chain stores and traditional stores. Hoover and Stotz re-computed the index without that linking procedure for five selected cities. Their results indicated that food prices rose 7.3 percent percentage points over the 1955-1961 period, compared to 8.0 percent for the corresponding CPI five-city average—a difference of about 0.1 percentage point per year.

Unquestionably the most important study of outlet bias in the CPI has been Marshall Reinsdorf's 1993 paper. After carefully reviewing the relevant theoretical and measurement considerations, Reinsdorf presents a comparison of prices in incoming and outgoing CPI rotation samples that is closely related to the method used in this paper.

[5] See, for example, Strople (2006).

During the 1987-1989 period he analyzed, the BLS introduced entirely new outlet and item samples in one-fifth of the CPI geographic areas each year. (We discuss the current four-year TPOPS rotation process in Section IV below.) Reinsdorf selected and pooled 35 reasonably homogeneous CPI food categories, such as flour, eggs, and butter, and computed the percentage changes in price between the old and new samples in 16 cities that underwent rotation during calendar year 1987 or July 1988-June 1989. For all areas pooled, the new sample average prices were 1.23 percent lower than the old sample average, that difference being statistically significant from zero at the five percent level. Given a five-year rotation cycle, this would imply an upward bias in the CPI food at home component of 0.25 percentage point per year. The estimate is an upper bound, however; it " … may possibly overstate the true outlet substitution bias because average quality in the new samples may have declined along with average prices"[6]. Reinsdorf obtained a similar difference for motor fuel, although that estimate was not statistically significant.

These results of Reinsdorf have provided the basis for almost all subsequent estimates of overall CPI new outlet bias. David Lebow, John Roberts, and David Stockton (1994) estimated that 40 percent of the CPI was subject to outlet bias; multiplying this by Reinsdorf's bias estimate for food and energy they obtained a 0.1 percentage point estimate for the CPI as a whole. Because of the possible effect of outlet quality differentials, their paper presented both a high-end bias estimate of 0.1 percentage point and a low-end estimate of zero. The Boskin Commission used Lebow *et al*.'s high-end 0.1 percentage point estimate in their report to the Senate Finance Committee.[7] Matthew Shapiro and David Wilcox (1996) elaborated on this by assigning a log-normal distribution to their outlet bias estimate, with a mean of 0.1 percentage point per year and 90 percent of its mass to the left of 0.2 percentage point. Finally, Lebow and Jeremy Rudd (2003) employed the 0.5 percentage point center of the Lebow-Roberts-Stockton range as their point estimate of new outlet bias, with a confidence interval ranging from zero to 0.2 percentage point annually.

In contrast to all these estimates, Jerry Hausman and Ephraim Leibtag have recently evaluated CPI new outlet bias using data from the ACNielsen Homescan survey. For our present purposes, their most relevant results are comparisons of prices between different store types, in 37 U.S. cities, for 20 relatively homogeneous grocery store food categories. These 20 item categories include thirteen that were also studied by Reinsdorf (1993). Pooling across the cities, Hausman and Leibtag computed the ratios of unit value average prices in traditional supermarkets to those in supercenters, mass merchandisers, and club stores (SMCs). The ratios averaged 1.300 and ranged as high as 2.117 (for lettuce). For only one item category—soda—was the ratio less than unity. Similar ratios with supermarkets replaced by all non-SMC stores were very similar.

Hausman and Leibtag (2004) go on to model the impact of growing SMC market penetration on market average prices and on the price responses of non-SMC stores. They conclude that annual CPI food-at-home inflation is too high by 0.32 to 0.42 percentage point. In Hausman and Leibtag (2005), they employ a discrete choice model

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[6] Reinsdorf (1993), p. 239.
[7] U.S. Senate (1996), p. 43.

of household shopping choice to conclude that the compensating variation value to consumers' of supercenter entry is 25 percent of food expenditure.

IV. Methodological Approach and Data

As we noted in Sections II and III, discussions of outlet bias in the CPI have focused on the differences in prices between incoming and outgoing outlets at the time of sample rotation. The Conference Board's Study Group on the CPI, for example, recommended that[8]:

> "When outlet rotation shows price changes on the same items between the old and new sales outlets, the BLS, instead of (as now) assuming that all of it represents differences in the quality and convenience of the transactions, should estimate what portion of the price change represents a difference in quality and convenience vs. what portion represents a "true" change in price."

Our primary goal in this paper is to determine the potential quantitative impact of changing the current BLS approach. For that purpose we examined CPI data on 20 sample-rotation months during the years 2002 through 2006. Our analysis was made possible by the BLS development of a CPI Research Data Base providing detailed information on the items priced in the index since 1987.[9] Previous studies have been limited by the difficulty of assembling large files of incoming and outgoing items along with their quality characteristics.

Following Reinsdorf (1993) and Hausman and Leibtag (2004), we initially selected a number of relatively homogeneous food categories in order to limit, as much as possible, the influence of differences across outlets in the characteristics of items being sold. These 14 categories are shown in Table 1. With the exception of non-carbonated juices and drinks, our list comprises those item categories that were studied by both Reinsdorf (1993) and Hausman and Leibtag (2004). Together, the CPI item strata in which these categories fall comprised approximately one-quarter of the weight of the Food at Home in the CPI in December 2006, although in the interest of maximizing homogeneity we have further limited some of the samples by including, for example, only yellow bananas within the Bananas item stratum. Even within these limited categories, our study differs from others by explicitly adjusting for the varying quality if goods sold by different outlet types. A large grocery store might sell name brand yellow bananas, while a discount department store might sell unbranded bananas.

Most of the categories above are what the CPI refers to as "Entry-Level Items" or ELIs, the ultimate sampling units for items as selected by the BLS national office. ELIs represent the level of item definition from which data collectors begin item sampling within each sample outlet.

As is true for the great majority of CPI items, the TPOPS rotation process brings in new outlet samples for these categories on a semi-annual basis, during four months of the year. The outlets chosen for pricing in each of the 87 areas in the CPI geographic sample

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[8] Conference Board (1999), p. 23.
[9] See Fixler and McClelland (2000), p. 6.

(primary sampling units or PSUs) are selected from frames generated using spending patterns reported in the household TPOPS survey, which is conducted for BLS by the Census Bureau. Within each CPI item category, the outlet sample is replaced in one-eighth of the areas during each semi-annual rotation; thus, the entire sample is replaced every four years.[10]

CPI PSUs are classified as either monthly or bimonthly according to the frequency of CPI price collection. New York, Chicago, and Los Angeles are monthly areas, indicating that BLS collects prices for virtually all item categories each month. In other areas, collection of most prices takes place only in odd or even months.[11] The relevance of this for present purposes is that in "bi-monthly odd" areas sample rotation typically occurs in May and September: those are the months in which both the incoming and outgoing samples are priced. In monthly and bi-monthly even areas, the overlap months are April and October. For example, in the bi-monthly even metropolitan area of San Francisco-Oakland-San Jose, the sample for soda was rotated in April 2004, coffee in April 2005, eggs and apples in October 2005, and bread in April 2006. By contrast, in Philadelphia-Wilmington-Atlantic City, coffee and eggs were rotated in April 2004, apples and bread in October 2004, and soda in October 2006. This balanced schedule smoothes the workload for CPI data collectors and, for our purposes, it yields a roughly constant number of incoming and outgoing item prices over our sample years.

In order to observe and compare the prices in the incoming and outgoing samples we confine our attention to the months of April, May, September, and October. For our empirical analysis we constructed a sample of all item prices—what the BLS calls "quotes"—in those four months for each of the years 2002 through 2006. For the 14 item categories above, this yields a total sample of 133,487 price quotes, or approximately 6,674 per month. Note that the same individual item in a given store will be observed in multiple months until it rotates out of the sample.

The CPI Research Database enables us to identify for each priced item the "business type" of store in which it is sold. Sample outlets are coded into hundreds of categories. Most of these categories—pet stores, banks, etc.—are not relevant for the items we study in this paper, but our data still provide great detail on store type. Roasted coffee, for example, is represented in our CPI sample primarily by three business types: Large Grocery Stores, Discount Department Stores (the supercenter category in which Wal-Mart would fall), and Warehouse Clubs and Other Membership Retail Outlets (which would include Sam's Club or Costco). Among the other store types represented are small grocery stores, chain drug stores, limited-service food service establishments (into which a Starbucks offering snacks would logically be classified), and miscellaneous food at home stores (such as a store selling only coffee), along with catalog and internet outlets. This detail enables us to obtain a clearer understanding of the impact of outlet type trends on the CPI than would be possible with a simple classification of outlets into, for example, traditional and non-traditional stores.

[10] The major exception to this process is rental housing, which is not subject to regular rotation. A few other "Non-POPS" items are rotated using other means. These items include, for example, postage and state vehicle registration. A more detailed discussion of pricing and sample rotation is given in Bureau of Labor Statistics (2007), pp. 13-17.

[11] The BLS prices food at home, energy, and selected other items on a monthly basis in all areas.

Figures 1 and 2 provide information on the distribution of outlet types in our sample and on the trends in the mix between 2002 and 2006. For most of the analyses in this paper we group outlets into six categories: Large Grocery Stores; Discount Department Stores; Warehouse Clubs and Other Membership Retail Outlets; Small Grocery Stores; Convenience Stores; and Other Outlet Types. The second and third of these categories comprise the SMC group discussed by Hausman and Leibtag. In Figure 1 we show the percentages of our total item sample by outlet category in each of our 20 sample months. Note that these are unweighted counts. For CPI index calculation, individual item prices will have different weights depending on their item stratum, their geographic area, and the specific way in which the probability sampling process was designed and carried out for that outlet and ELI. For our purposes, however, the use of unweighted counts is both more convenient and more useful.

As Figure 1 demonstrates, the aggregate market share of the five outlet categories other than Large Grocery Stores in our CPI food samples has been growing steadily, from about 17 percent in April 2002 to about 25 percent in October 2006. The two SMC categories have exhibited the most striking growth. Discount Department Stores increased from 3.4 percent to 9.0 percent, and Warehouse Club stores from 3.4 percent to 6.4 percent. Among the three remaining categories, an increase in the small share of Convenience Stores (from 0.9 percent to 1.5 percent) partially offset small declines for Small Grocery Stores and for Other Outlets.

The aggregate 15.4 percent share of SMCs in the last year of our data of approaches, but is somewhat lower than, the share reported by the federal government's Economic Research Service (ERS) for all sales of food at home. According to ERS, warehouse clubs, supercenters, and mass merchandisers accounted for 19.6 percent of food at home sales in 2006. The unavoidable lags in the TPOPS rotation process may account for some of this difference.

Figure 2 demonstrates that the growth in the share of SMCs in our sample has not been limited to any one item category. In that figure we compare the percentages of quotes priced in SMCs for the first and last years of our study period, and show that those percentages increased sharply in each of our 14 categories.

Despite the large overall size of our sample, the limited numbers of observations at the item-area level do not permit straightforward, definitive comparisons of the levels of incoming and outgoing prices. A representative sample size for an item category in our analysis in an overlap month is about 425 quotes, of which about 50 quotes would comprise the typical incoming and outgoing samples in the PSUs undergoing rotation (with 25 quotes out of 400, one-sixteenth of the sample, being replaced in a month). Even in homogeneous item categories like the ones we study, two samples of 25 quotes each are insufficient to yield significant tests of differences in mean prices, given the random variation due to temporary sales, random changes in package sizes, neighborhood locations and outlet categories, and other factors. Note also that the growth in the share of supercenters and other discount outlets, although significant, is gradual. Supercenters might be expected to account for perhaps five of the 25 quotes in an incoming sample compared to two in the outgoing sample that was introduced four years earlier. Such differences cannot be expected to have consistent dramatic powerful impacts in mean prices in individual area rotation samples.

Even at the national level for an item category, we observed great volatility in the ratios of mean prices between samples in rotation months. This does not mean, however, that the changes in outlet type do not have an important effect on price levels, only that it is difficult to observe that effect in individual monthly samples using only sample average prices. Therefore, in the next section we report on a multiple regression approach that pools across location and time and that adjusts for observable differences in product characteristics.

V. Regression Results

We begin with a regression specification that includes only location, time, store type, and variables indicating whether the observed price was a sale price. Log-linear models of the following form were estimated:

$$\begin{aligned}\ln P_{it} &= \beta_0 + \beta_1 DD_{it} + \beta_2 SG_{it} + \beta_3 Co_{it} + \beta_4 Wa_{it} + \beta_5 Ot_{it} \\ &+ \beta_6 DDS_{it} + \beta_7 SGS_{it} + \beta_8 CoS_{it} + \beta_9 WaS_{it} + \beta_{10} OtS_{it} + \beta_{11} LGS_{it} \\ &+ \sum_t \delta_t D_t + \sum_a \delta_a D_a + u_{it}\end{aligned} \tag{7}$$

where DD and DDS are dummy variables indicating regular and sale prices, respectively, at discount department stores, SG and SGS indicate regular and sale prices at small grocery stores, Co and CoS indicate regular and sale prices at convenience stores, Wa and WaS indicate prices at warehouse and club stores, Ot and OtS indicate prices at outlets of all remaining outlet types and LGS indicates large grocery sale prices. The omitted category comprises items sold at regular prices at large grocery stores, so that coefficient estimates represent differences from regular prices at large grocery stores. The variables D_t and D_a indicate that the price was gathered in month *t* in CPI index area *a*.

The results for the variables of interest are listed in table 2. The first column of the table, for example, shows that regular prices for bread in discount department stores are about 77% ($e^{-.255} = .775$) of regular prices in large grocery stores. Prices at warehouse and club stores are about 39 percent lower than regular prices in large grocery stores.

In interpreting these results, it is important to note that the dependent variables are measured on a per-unit basis, consistent with CPI practice for food items. For example, the dependent variables in the soda and coffee regressions are the logarithms of price per ounce and price per pound, respectively. Thus, variations in package size across items and outlets will not affect the price variable directly. Indirectly, however, the per-unit price may well vary with package size if markets are characterized by volume discounts.

Looking across all the item categories, the absolute values of most outlet type coefficient estimates are more than twice their standard errors, indicating that the associated outlet type has average prices that are significantly different from those charged by large grocery stores when time period and area location are held constant. Regular prices at discount department stores and warehouse/club stores are estimated to be markedly and significantly lower than at large grocery stores in almost all item categories, while the results for small groceries, convenience stores, and other store types are less consistent. Within the SMC category, warehouse/club prices are usually lower than discount department store prices. The adjusted R^2 values of the regressions in table 2 range from

.10 (non-carbonated drinks) to .51 (butter), probably reflecting the greater heterogeneity within the former category.

The table also highlights the role of sale prices. Our regression indicates that sale prices for bread at large grocery stores are about 22 percent lower than regular prices at those stores. This makes those sale prices comparable to regular prices at discount department stores and offsets about half the gap *vis-à-vis* warehouse/club prices. Sale prices for bread are relatively rare at discount department stores in our data and we observed none at warehouse/club stores. Across all 14 item categories, the Table 2 results indicate that sale prices at large grocery stores are lower than regular prices at discount department stores for 12 of 14 categories. We emphasize, therefore, that both the outlet coefficients and outlet/sale coefficients must be taken into account in interpreting the results of our regressions.

Figure 3 demonstrates the differential incidence of sales for the three outlet categories of most interest, in our price sample as a whole. Interestingly, the share of sales is not only highest in the Large Grocery Store category, it increases monotonically from year to year. In sharp contrast, sale prices show a monotonic decline in relative frequency in the Discount Department Store category. This divergence may reflect systematic marketing strategies by the two categories as the share of supercenters grows. Examining such a possibility is beyond the scope of this paper, however. Finally, and not surprisingly, the share of sales at Warehouse/Club stores is very small in every year.

Although the items used here are relatively homogeneous, an important purpose of this paper is to determine whether some of the variation in prices across outlets arises from variation in the average quality of items sold at those outlets. For example, if discount department stores sell items with lower average quality than those sold at large grocery stores, then the difference in the quality adjusted prices between those store types would be smaller.

To address that possibility, we re-estimated the 14 table 2 equations adding dummy variables for item characteristics. Each ELI has one or more checklists that allow BLS employees to locate and price the same item in successive periods. We display the checklist for tomatoes in the appendix as an example. The checklists include categories for most relevant characteristics, and several additional write-in categories. For tomatoes, this includes such information as the variety of tomato (cherry, plum, etc.), whether the tomatoes are organic, whether they are greenhouse-grown, and whether they are loose or packaged. For other items, container size will be a particularly important characteristic. Here we employ dummy variables for virtually all non-write-in checklist categories for each ELI. The outlet-related coefficient results and regression summary statistics are shown in Table 3.

Comparison of tables 2 and 3 reveals several important results. First, the table 3 regressions have far greater explanatory power, reflecting the strong influence of the item quality variables on per-unit price. The average adjusted R^2 across the 14 regressions in Table 3 is 0.612, compared with an average of 0.320 in Table 2. The most dramatic increases are for soda and non-carbonated beverages, with adjusted R^2 increases of 0.51 and 0.62, respectively. The smallest increase (.014) is in the extremely homogeneous category of iceberg lettuce.

The second difference of most interest between the tables is the frequent decrease in the estimated price differential for discount department stores relative to large grocery stores. In 11 of 14 item categories, the coefficient for non-sale discount department store prices is closer to zero in Table 3 than in Table 2. Using bread again as an example, the estimated differential of 23 percent from Table 2 is reduced to 16 percent in Table 3 when item quality specifications are held constant. We conclude that, on average, item quality is lower in discount department stores. The same does not hold for warehouse/club stores. In only six of 14 categories does the inclusion of item characteristic variables reduce the estimated price differential between warehouse/club stores and large grocery stores. We also observe that the estimated discount for sale prices at large grocery stores falls in Table 3 relative to Table 2, suggesting that lower-quality items are the ones most likely to be on sale at those stores. Meanwhile, although regular prices are estimated to be lower at discount department stores than at large grocery stores in all 14 item categories, it is also the case that sale prices at large grocery stores are estimated to be even lower than regular prices at discount department stores in all 14 categories.

Using the unweighted means across the item categories of the log-price coefficients in Table 3, we estimate that holding item specifications, area location, and time period constant, regular prices are lower than those charged at large grocery stores by 15 percent at discount department stores and by 26 percent at warehouse/club stores. At large grocery stores, sale prices are lower than regular prices by an average of 25 percent.

Small grocery store regular prices are lower than large grocery regular prices in 12 item categories and by an average of 11 percent. The results for the convenience and other store categories vary more widely by item.

VI. Simulated Outlet Rotation Effects

We have demonstrated that the shares of discount store types have been growing rapidly in CPI food data. We have also shown that prices in these store types are significantly lower than in the dominant traditional outlet category, large grocery stores, albeit by a smaller margin once detailed item characteristics are taken into account. We next turn to the question of whether the introduction of lower-priced outlets would significantly reduce measured food inflation if BLS procedures were modified in the way that some experts have recommended. That is, if the BLS replaced its implicit assumption that differences in quality account for across-store differences in prices with the assumption that the differences in quality are irrelevant, would the impact be large enough to affect the CPI?

In equation (6) in Section II we decomposed the CPI measure of price change across an outlet sample rotation into two terms, to show how the BLS "links out" the effect of a changing mix of sample outlets. The second term in the equation was the inner product of the log prices charged in each of a set of S outlet categories in the rotation month *t*, multiplied by the changes in market shares of those categories between the old and new samples. This term, which we can refer to as the "outlet effect" OE, is given by

$$OE_t = \sum_{k=1}^{S} (V_k - W_k) \ln\left(\overline{P}_{k,t}\right) \tag{8}$$

If we denote the share of the sample subject to rotation in month *t* as *r*, equation (8) can be rewritten as

$$OE_t = r\sum_{k=1}^{S}(N_k - O_k)\ln\left(\overline{P}_{k,t}\right) \tag{9}$$

where N_k and O_k represent the shares of outlet category *k* in the sets of incoming and outgoing outlets, respectively.

Once again, the outlet effect OE will not contribute to the CPI measure of inflation between periods *t-1* and *t+1*. Implicitly, the differences in prices across outlet types are viewed as due to differences in quality. In the alternative view, OE should be included in the inflation measure because consumers benefit from the lower average prices in the newer outlets.

Using the regression results we reported above, we can estimate the importance of the outlet effect for each of our 14 item categories. Let outlet category 1 be Large Grocery stores. Then, since the sum of the changes in outlet shares must sum to zero, we can rewrite equation (9) as

$$OE_t = r\sum_{k=2}^{S}(N_k - O_k)\left[\ln\left(\overline{P}_{k,t}\right) - \ln\left(\overline{P}_{1,t}\right)\right] \tag{10}$$

We then replace the log-difference in prices between outlet categories (recall that in Section II, for convenience of exposition, prices were assumed to be constant within categories) by the estimates of outlet category price differences taken from our log-linear regressions. We re-estimated our regressions without the sale-price dummy variables so that the outlet-category dummies would provide estimated average log-differences across categories, with the area, time period, and—most importantly—item quality variables held constant. The different impacts and frequencies of sale prices within the outlet categories are subsumed in the outlet-category coefficients. (The results of these regressions are not reported here but are available on request.) Referring to the category dummy coefficients as β_k, we can now write the outlet effect as

$$OE_t = r\sum_{k=2}^{S}(N_k - O_k)\beta_k \tag{11}$$

In equation (11), the terms in the summation will measure the separate impacts of changes in the shares of each outlet category. If a category has the same share in the incoming and outgoing outlets, its effect will be zero.

An example of this process is shown in Table 4, for the Coffee outlet category. The values of *N* and *O* used in the table are the unweighted average values, pooling the data for all our rotation months, of the outlet category shares in the incoming and outgoing outlets for that item category. Because we do not multiply by the *r* term, the estimate of the outlet effects corresponds to an entire sample rotation cycle, which is four years in current CPI practice.[12] For example, discount department stores made up 11.29 percent

[12] In taking these unweighted averages we ignore some complexities of our data. For example, in any given area, month, and item category the numbers of incoming and outgoing items will not be the same, due to sample attrition and changes in the CPI's sample allocation parameters. Some of the months in our study

of the incoming rotation quotes for Coffee, compared to 8.24 percent of outgoing quotes. The regression estimate (with no sale price variables) of the log-price differential between discount department stores and large grocery stores is -.170. Assuming a complete rotation of the sample, we then estimate that the effect on the average per-ounce price of roasted coffee of the increased share of discount department stores would be (.1129 - .0824) (-.170) or -0.52 percent.

Table 4 also shows these effects for the rest of the store categories relative to large grocery stores, the reference category, whose share fell from 73 percent in outgoing samples to 65 percent in incoming samples. Notice that for coffee warehouse/club stores have a stronger negative impact than discount department stores; although their market share increase was less than for discount department stores, their estimated price differential was much greater. The table also demonstrates a strong offsetting impact of the other-store category, which would include specialty stores featuring coffee. These stores had significantly higher prices as well as an increasing share of the market. Despite this offset, the changing mix of outlets is estimated to have a downward impact of 1.18 percent on coffee prices over a complete sample rotation.

Table 5 summarizes these outlet rotation effects for all 14 item categories we studied. For the major outlet categories of interest the results display a great deal of consistency. Discount department stores have a negative impact in all 14 categories, for an unweighted average of -0.53 percent. Warehouse/club stores have negative impacts in 12 of 14 item categories, the average effect being slightly larger than for discount department stores. Small grocery stores have negative effects except for bananas and ground beef. For convenience stores and other stores, the estimated effects are also negative although erratic and, in aggregate, small. The positive effect of other store types on coffee prices was mentioned in the previous paragraph. For convenience stores, the most notable impact is negative, in the soda category. Soda prices are significantly higher in convenience stores, but their market share is only 2.5 percent in incoming samples compared to 5.3 percent in outgoing samples.

Summing over all outlet types relative to large grocery stores, the impact of outlet mix changes is negative for all item categories, with total impacts ranging very widely from -0.02 percent (potatoes) to -3.72 percent (tomatoes). For all items taken together, the mean impact is -1.36 percent, which would translate into -0.34 percent per year assuming a four-year rotation cycle.

To establish whether these estimated outlet mix effects are statistically significant, we used a bootstrap procedure. For each item category, we selected 999 bootstrap samples, by drawing randomly with replacement from the original sample. The bootstrap samples were equal in size to the full sample. In each sample we re-estimated the regression and recalculated the total effects of the type reported in Tables 4 and 5. We then computed 95 percent confidence intervals for the total outlet mix effects. These confidence intervals are reported in the last two columns of Table 5. For eight of the 14 item

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period also had a greater rotation rate than others. The results in Table 4, therefore, do not precisely represent the outlet effect over any time period. We know of no reason for them to present a quantitatively biased picture, however.

categories, the upper bound of the confidence interval is negative, indicating that the negative estimate of the outlet mix effect is statistically significant at the 5 percent level.

VII. Concluding Remarks

This paper confirms the potential importance of new outlets bias in the CPI. Using CPI data for 2002-2006, we observe a continuous increase in the market share of SMCs: discount department stores and warehouse/club stores. We also observe significantly lower prices at those stores than at large grocery stores, even after adjusting for a large number of item characteristics. We estimate that given a four-year rotation cycle, allowing outlet price differentials to be reflected in the CPI would lower the measured rate of inflation by between 0.3 and 0.4 percentage point per year in the 14 item categories we study. However, using bootstrap methods we conclude that the outlet mix effect is statistically significant in just eight of the 14 item categories. We believe that these results constitute an important update and extension of the prior work on this topic.

We emphasize, however, that this is by no means conclusive evidence of CPI bias. Our analysis holds observable item characteristics constant, but does not address outlet characteristics such as locational convenience, service quality, and item selection variety. Only by assuming that consumers are indifferent among stores on these dimensions can our results be taken at face value. Certainly, the fact that the market shares of SMCs are growing suggests that many consumers are benefiting from the lower prices at those stores. However, our results also show some countervailing trends, such as the increasing market share of outlet types that sell coffee at higher than average prices. Consumers shifting to those stores must attach some value either to the characteristics of those outlet types or to unmeasured characteristics of the items sold there. In addition, warehouse and club stores have lower average prices than discount department stores in most of the items studied, but the share of sales to discount department stores have grown faster than the share of sales to warehouse and club stores. Thus, our results suggest that outlet characteristics are not negligible factors.

We also found that sale prices at large grocery stores are comparable in many cases to regular prices at discount department stores, and that sale prices are becoming more frequent at large grocery stores and less frequent at SMCs. In shopping at traditional stores, therefore, consumers may be opting for locational convenience or other aspects of “outlet quality” in return for having to manage the timing of their purchases to match the timing of item sales. In future research we plan to analyze this issue of outlet quality further.

Appendix
CPI Tomatoes Checklist

```
BUREAU OF LABOR STATISTICS            U.S. DEPARTMENT OF LABOR
 CONSUMER PRICE INDEX - ELI CHECKLIST
 collection             outlet                      quote          arranging
 period: __ __ __ __    number: __ __ __ __ __ __ __ code: __ __ __  code:    __ __ __ __
 ______________________________________________________________________________________
 ELI No./                                                                cluster
 title        FL031 TOMATOES                                              code   01A
 item availability:    1-AVAILABLE    2-ELI NOT SOLD     3-INIT INCOMPLETE
 purpose of checklist: 1-INIT   2-INIT COMPL  3-SPEC CORR   4-SUB   5-REINIT   6-CHECK REV
 ______________________________________________________________________________________
 CURRENT PERIOD                               | SALES TAX
                                              |
   price: _ _ _ _ _ _ . _ _ _                 |      included:        YES    NO
                                              |
   type of price:  REG   SALE                 |
                                              |
   quantity:  __ __ __                        |
                                              |
   size:  _ _ _ _ . _ _ _    pair:  YES    NO |
                                              |
   unit of size: ______________               |
                                              |
 _____________________________________________|
             |
 YEAR-ROUND  |  in-season:  JAN  FEB  MAR  APR  MAY  JUN  JUL  AUG  SEP  OCT  NOV  DEC
 ____________|_________________________________________________________________________
 respondent:                                  location:
 ______________________________________________________________________________________
 field message:
 ______________________________________________________________________________________
```

VARIETY
- A1 Cherry Tomatoes
  - B1 Grape tomatoes
  - B98 Other (if specified), ______________________________
- A2 Round Red (Regular or Slicing) Tomato Varieties
  - ** B2 Variety of Round Red Not Specified
  - ** B99 Specified variety, ______________________________
- A3 Plum/Roma/Italian
- A97 Other, ______________________________

TYPE
- C1 Field Grown/Vine Ripe
- C2 Green House/Hot House
  - ** D2 Hydroponic
  - ** D98 Other (if specified), ______________________________
- C3 Not specified/Unable to determine
- C99 Other, ______________________________

ORGANIC CERTIFICATION
- E1 Not USDA Certified organic
- E2 USDA Certified organic
- E3 Other Organic Claim

**** PACKAGING**
- F1 Loose
- F2 Packaged (Box, Tray, etc.)

**** SIZE REPRESENTS**
- G1 Weight labeled
- G2 One Package Weighed (Qty. = the # of packages priced)
- G3 Weighed 2 Tomatoes, circled YES for PAIR (Qty. = the # of tomatoes priced)

OTHER FEATURES
- H99 ______________________________
- I99 ______________________________

**** OTHER ITEM IDENTIFIERS**
- J99 ______________________________
- K99 ______________________________
- L99 ______________________________

Figure 1
Market Shares by Outlet Type

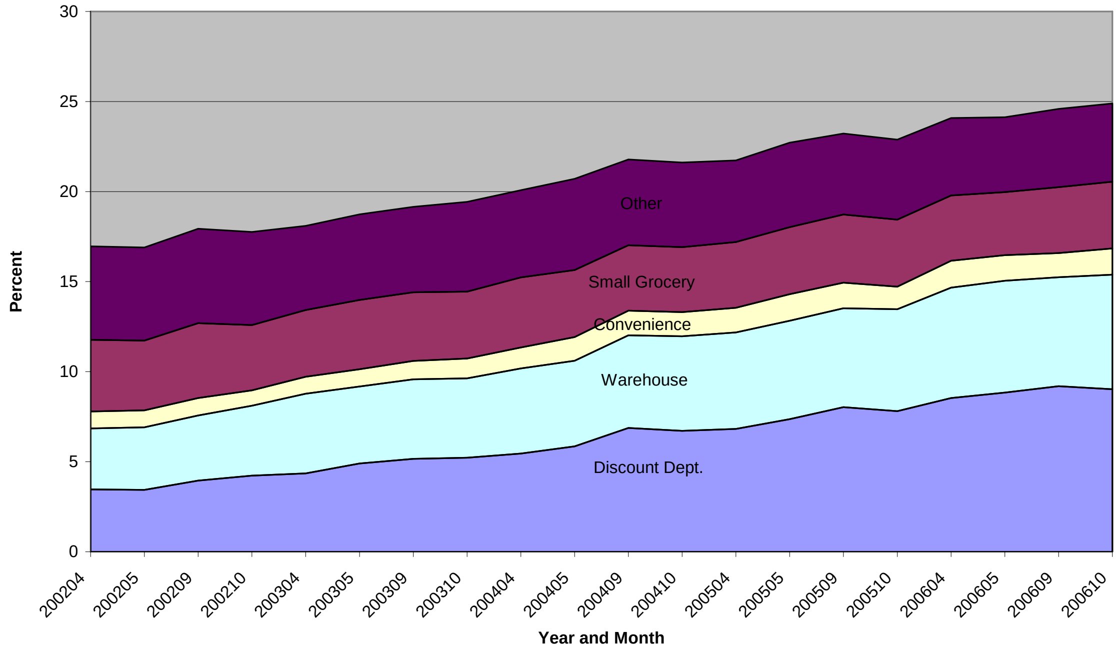

Figure 2
SMC Shares by Item Category, 2002 and 2006

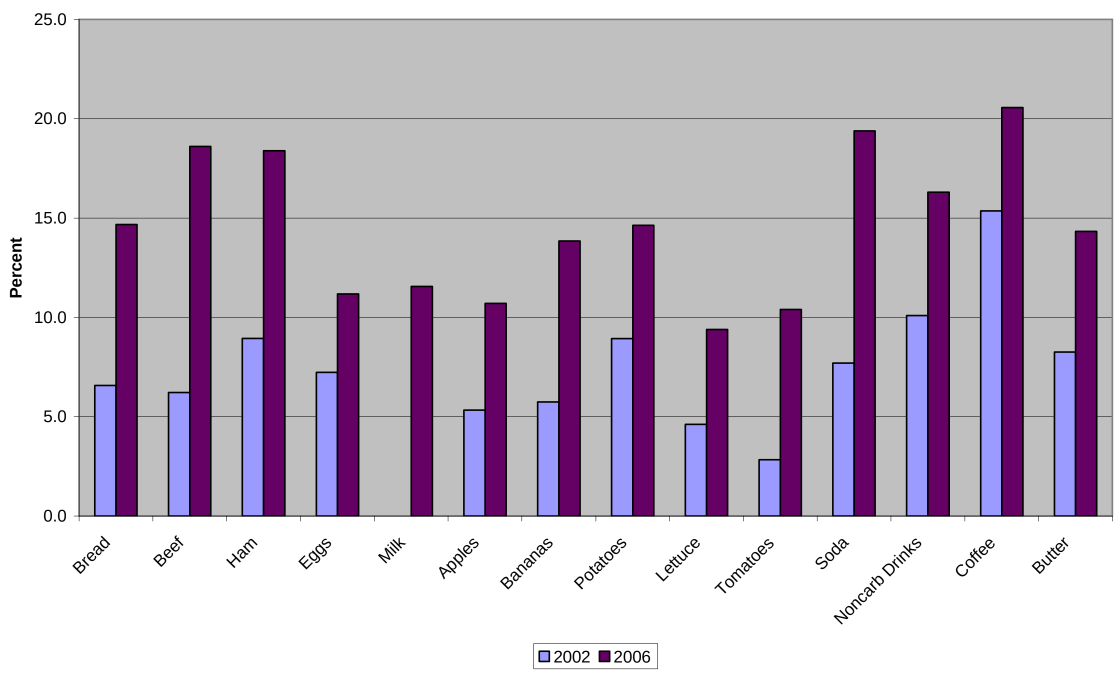

Figure 3
Percent of Items on Sale
By Outlet Type and Year

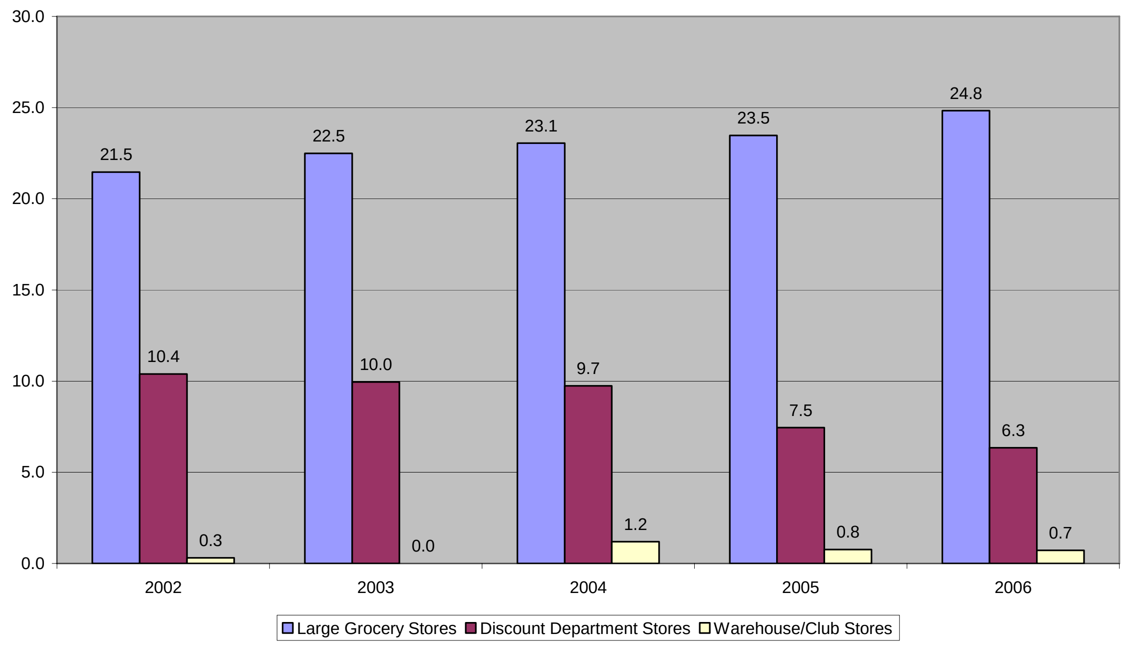

Table 1. Item Categories

White Bread
Yellow Bananas
Chicken Eggs
Ground Beef
Ham, Excluding Canned
Apples
Fresh Whole Milk
Potatoes
Tomatoes
Soda
Non-carbonated Juices and Drinks
Roasted Coffee
Butter
Iceberg Lettuce

Table 2. Regressions Estimates, No Item Specification Variables

Panel A

	Item Category						
Outlet Type	Bread	Bananas	Eggs	Beef	Ham	Apples	Milk
Discount Department	-0.255	-0.190	0.015	-0.189	-0.213	-0.143	-0.070
	0.023	*0.012*	*0.023*	*0.011*	*0.030*	*0.011*	*0.020*
Small Grocery	-0.197	0.058	-0.168	-0.155	-0.072	-0.242	-0.049
	0.028	*0.016*	*0.027*	*0.014*	*0.024*	*0.013*	*0.026*
Convenience	-0.121	0.127	-0.058	-0.119	0.395	-	0.108
	0.055	*0.034*	*0.046*	*0.068*	*0.097*	*-*	*0.022*
Warehouse	-0.498	-0.559	0.274	-0.443	-0.153	-0.446	-0.458
	0.038	*0.013*	*0.022*	*0.011*	*0.018*	*0.016*	*0.034*
Other	-0.166	-0.094	0.132	-0.028	0.195	-0.456	-0.032
	0.020	*0.015*	*0.045*	*0.012*	*0.025*	*0.012*	*0.035*
Large Grocery, Sale	-0.251	-0.338	-0.289	-0.269	-0.421	-0.352	-0.259
	0.015	*0.007*	*0.016*	*0.007*	*0.015*	*0.007*	*0.016*
Discount Department, Sale	-0.256	-0.150	-0.181	-0.144	-0.192	-0.295	-0.514
	0.062	*0.052*	*0.102*	*0.052*	*0.105*	*0.034*	*0.073*
Small Grocery, Sale	-0.117	-0.258	-0.226	-0.338	-0.330	-0.183	-0.105
	0.093	*0.045*	*0.079*	*0.040*	*0.069*	*0.030*	*0.069*
Convenience, Sale	-0.146	-	-0.422	-0.344	-0.661	-	-0.116
	0.138	*-*	*0.133*	*0.270*	*0.313*	*-*	*0.105*
Warehouse, Sale	-	-0.558	-0.368	-0.135	-0.130	-0.337	-
	-	*0.116*	*0.251*	*0.063*	*0.191*	*0.173*	*-*
Other, Sale	-0.397	-0.189	-0.407	-0.200	-0.353	-0.174	-0.438
	0.081	*0.055*	*0.125*	*0.042*	*0.096*	*0.042*	*0.131*
Sample Size	8,001	9,304	9,384	12,723	7,285	17,615	4,072
R^2	0.1873	0.5012	0.3451	0.3261	0.2443	0.3144	0.2674

Standard errors are in italics

Table 2. Regressions Estimates, No Item Specification Variables

Panel B

	Item Category						
Outlet Type	Potatoes	Tomatoes	Soda	Non-Carbonated	Coffee	Butter	Lettuce
Discount Department	-0.238	-0.219	-0.236	-0.292	-0.175	-0.320	-0.201
	0.028	*0.024*	*0.011*	*0.025*	*0.020*	*0.023*	*0.020*
Small Grocery	-0.443	-0.259	0.062	0.043	-0.195	-0.092	-0.010
	0.030	*0.024*	*0.018*	*0.043*	*0.037*	*0.027*	*0.024*
Convenience	-0.448	-0.225	0.504	0.308	0.490	-0.152	0.086
	0.104	*0.067*	*0.018*	*0.044*	*0.095*	*0.061*	*0.048*
Warehouse	-0.522	-0.425	-0.217	-0.349	-0.451	-0.778	0.145
	0.027	*0.031*	*0.016*	*0.024*	*0.024*	*0.020*	*0.133*
Other	-0.289	-0.566	0.384	0.024	0.813	-0.258	-0.164
	0.029	*0.022*	*0.018*	*0.036*	*0.018*	*0.037*	*0.029*
Large Grocery, Sale	-0.423	-0.369	-0.270	-0.267	-0.308	-0.322	-0.353
	0.016	*0.012*	*0.007*	*0.014*	*0.015*	*0.012*	*0.013*
Discount Department, Sale	-0.277	-0.262	-0.130	-0.002	-0.428	0.161	-0.187
	0.086	*0.066*	*0.028*	*0.099*	*0.077*	*0.093*	*0.060*
Small Grocery, Sale	-0.119	-0.440	-0.199	-0.083	-0.221	-0.355	-0.426
	0.072	*0.047*	*0.042*	*0.115*	*0.127*	*0.057*	*0.044*
Convenience, Sale	-0.072	-0.138	-0.474	-0.248	-	-	-0.487
	0.348	*0.126*	*0.052*	*0.250*	*-*	*-*	*0.299*
Warehouse, Sale	0.334	-	-0.160	-0.769	-0.785	-	-
	0.469	*-*	*0.271*	*0.326*	*0.322*	*-*	*-*
Other, Sale	0.139	-0.242	-0.539	-0.370	-0.940	-0.090	-0.182
	0.068	*0.072*	*0.033*	*0.096*	*0.100*	*0.189*	*0.074*
Sample Size	7,930	10,598	17,208	13,195	7,269	3,803	4,773
R^2	0.3060	0.2568	0.2480	0.0969	0.4612	0.5100	0.4122

Standard errors are in italics

Table 3. Regressions Estimates, With Item Specification Variables

Panel A

	Item Category						
Outlet Type	Bread	Bananas	Eggs	Beef	Ham	Apples	Milk
Discount Department	-0.179	-0.180	-0.142	-0.159	-0.205	-0.144	-0.035
	0.018	*0.011*	*0.020*	*0.009*	*0.021*	*0.010*	*0.012*
Small Grocery	-0.162	-0.029	-0.147	-0.100	-0.164	-0.250	-0.032
	0.022	*0.016*	*0.023*	*0.012*	*0.017*	*0.011*	*0.016*
Convenience	-0.131	0.038	-0.064	-0.015	-0.053	-	0.056
	0.042	*0.033*	*0.038*	*0.056*	*0.068*	-	*0.014*
Warehouse	-0.506	-0.486	-0.293	-0.468	-0.240	-0.162	-0.274
	0.031	*0.013*	*0.023*	*0.009*	*0.013*	*0.016*	*0.021*
Other	-0.245	-0.065	0.087	-0.041	0.229	-0.450	-0.045
	0.019	*0.014*	*0.042*	*0.010*	*0.018*	*0.011*	*0.021*
Large Grocery, Sale	-0.219	-0.332	-0.276	-0.231	-0.344	-0.354	-0.201
	0.012	*0.006*	*0.013*	*0.005*	*0.010*	*0.006*	*0.010*
Discount Department, Sale	-0.266	-0.137	-0.219	-0.105	-0.300	-0.316	-0.381
	0.048	*0.049*	*0.085*	*0.042*	*0.073*	*0.030*	*0.043*
Small Grocery, Sale	-0.080	-0.181	-0.153	-0.317	-0.361	-0.188	-0.055
	0.072	*0.042*	*0.066*	*0.032*	*0.048*	*0.027*	*0.041*
Convenience, Sale	-0.204	-	-0.487	-0.297	-0.342	-	-0.302
	0.106	-	*0.111*	*0.220*	*0.217*	-	*0.062*
Warehouse, Sale	-	-0.507	-0.496	-0.099	-0.015	-0.150	-
	-	*0.107*	*0.210*	*0.052*	*0.132*	*0.155*	-
Other, Sale	-0.435	-0.111	-0.381	-0.103	-0.349	-0.204	-0.190
	0.064	*0.054*	*0.104*	*0.034*	*0.067*	*0.038*	*0.078*
Sample Size	8,001	9,304	9,384	12,723	7,285	17,615	4,072
R^2	0.5213	0.5741	0.5446	0.5529	0.6365	0.4506	0.7441

Standard errors are in italics

Table 3. Regressions Estimates, With Item Specification Variables
Panel B

Outlet Type	Potatoes	Tomatoes	Soda	Non-Carbonated	Coffee	Butter	Lettuce
	Item Category						
Discount Department	-0.073	-0.209	-0.144	-0.238	-0.221	-0.235	-0.185
	0.018	*0.019*	*0.007*	*0.014*	*0.016*	*0.020*	*0.020*
Small Grocery	-0.260	-0.230	0.063	0.001	-0.256	-0.123	-0.018
	0.020	*0.018*	*0.011*	*0.025*	*0.028*	*0.023*	*0.024*
Convenience	-0.253	-0.188	0.182	0.272	0.365	-0.010	0.081
	0.068	*0.051*	*0.011*	*0.026*	*0.073*	*0.052*	*0.048*
Warehouse	0.095	-0.622	-0.213	-0.381	-0.558	-0.357	0.158
	0.022	*0.025*	*0.011*	*0.016*	*0.019*	*0.032*	*0.132*
Other	-0.348	-0.493	0.167	0.003	0.383	-0.196	-0.169
	0.019	*0.017*	*0.011*	*0.021*	*0.016*	*0.031*	*0.029*
Large Grocery, Sale	-0.351	-0.346	-0.223	-0.275	-0.286	-0.279	-0.359
	0.010	*0.009*	*0.004*	*0.008*	*0.012*	*0.011*	*0.012*
Discount Department, Sale	-0.115	-0.281	-0.123	-0.058	-0.172	0.137	-0.200
	0.056	*0.050*	*0.016*	*0.056*	*0.057*	*0.079*	*0.060*
Small Grocery, Sale	-0.149	-0.319	-0.265	-0.174	-0.227	-0.336	-0.423
	0.047	*0.036*	*0.024*	*0.064*	*0.095*	*0.049*	*0.044*
Convenience, Sale	-0.063	-0.115	-0.323	-0.132		-	-0.483
	0.226	*0.095*	*0.030*	*0.140*		*-*	*0.296*
Warehouse, Sale	0.229	-	-0.170	-0.418	-0.619	-	-
	0.305	*-*	*0.155*	*0.181*	*0.240*	*-*	*-*
Other, Sale	-0.080	-0.228	-0.391	-0.227	-0.557	-0.117	-0.172
	0.044	*0.055*	*0.019*	*0.054*	*0.076*	*0.167*	*0.074*
Sample Size	7,930	10,598	17,208	13,195	7,269	3,803	4,773
R^2	0.7077	0.5757	0.7557	0.7222	0.7018	0.6531	0.4257

Standard errors are in italics

Table 4. Outlet Effects for Roasted Coffee

	Outlet Type					
	Discount Department	Small Grocery	Convenience	Warehouse	Other	Total
Incoming Sample Share (N)	11.29%	3.63%	0.40%	8.47%	11.29%	35.08%
Outgoing Sample Share (O)	8.24%	2.23%	0.45%	6.46%	9.80%	27.17%
Log Price, Relative to Large Grocery Stores (β)	-0.170	-0.211	0.427	-0.492	0.432	
Store Type Effect ([N-O]β)	-0.52%	-0.30%	-0.02%	-0.99%	0.64%	-1.18%

Table 5. Outlet Effects by Item Category

Item Category	Outlet Type: Discount Dept. Stores	Small Grocery Stores	Convenience Stores	Warehouse/Club Stores	Other Store Types	Total Effect	Confidence Interval (95%) for Total Effect: Lower	Upper
Bread	-1.37%	-0.13%	-0.04%	-0.08%	-0.93%	-2.55%	-3.87%	-1.15%
Bananas	-0.80%	0.01%	0.03%	-1.15%	-0.02%	-1.93%	-3.05%	-0.76%
Eggs	-0.53%	-0.13%	-0.06%	-0.46%	0.10%	-1.07%	-1.99%	-0.13%
Beef	-0.70%	0.26%	0.01%	-1.26%	0.00%	-1.68%	-2.61%	-0.76%
Ham	-0.65%	-0.09%	0.00%	-0.66%	-0.54%	-1.95%	-3.14%	-0.78%
Apples	-0.25%	-0.42%	0.00%	-0.22%	-0.35%	-1.25%	-2.13%	-0.38%
Milk	-0.16%	-0.06%	-0.18%	0.10%	-0.03%	-0.34%	-1.25%	0.53%
Potatoes	-0.08%	-0.28%	0.15%	-0.31%	0.51%	-0.02%	-1.21%	1.20%
Tomatoes	-0.63%	-0.93%	0.02%	-2.04%	-0.14%	-3.72%	-5.23%	-2.23%
Soda	-0.31%	-0.08%	-0.66%	-0.02%	-0.03%	-1.10%	-1.68%	-0.47%
Non-Carbonated	-0.49%	-0.01%	0.28%	-0.44%	0.03%	-0.62%	-1.56%	0.18%
Coffee	-0.52%	-0.30%	-0.02%	-0.99%	0.64%	-1.18%	-4.33%	1.92%
Butter	-0.33%	-0.18%	0.00%	-0.91%	-0.10%	-1.51%	-3.37%	0.45%
Lettuce	-0.61%	-0.11%	-0.02%	0.00%	0.59%	-0.15%	-1.06%	0.83%
Average	-0.53%	-0.17%	-0.03%	-0.60%	-0.02%	-1.36%	-2.61%	-0.11%

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