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# Price Differentials Across Outlets in Consumer Price Index Data, 2002-2007

by

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**Abstract**

In this paper we provide new evidence on the impact on the U.S. CPI of the appearance and growth of new types of product outlets. We find that the changing mix of outlet types between 2002 and 2007 had a statistically significantly negative impact on average prices in most of the 14 item food categories we study. Our approach allows us to examine the effects of changes in outlet mix both across outlet types (such as between large groceries and discount department stores) and within those outlet categories. We also adjust for numerous differences in item characteristics such as brand name and organic certification. In our sample we find that the upward impact on price from increased item quality has offset most of the downward impact of lower-priced outlets.

## 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 2007. 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. 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, we find that CPI food samples exhibited a steadily increasing share of prices from discount department stores and from warehouse and club stores. We observe this trend for each of the 14 item categories we study. 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 samples.

We analyze the new outlets issue by estimating, for each of our 14 item categories, a regression model in which the price of an item is a function of variables representing time and item characteristics, plus fixed effects for each of our sample outlets. This enables us to perform statistical tests of whether these outlet fixed effects vary over time and thereby whether outlet mix affects the estimate of price change. We find that the changing mix of outlet types between 2002 and 2007 had a statistically significantly negative impact on average prices in most of the 14 item categories. Our approach also allows us to examine the effects of changes in outlet mix both across outlet types (such as between large groceries and discount department stores) and within those outlet categories. We find that within-category changes account for more than a third of the total outlet effect.

We also are able to adjust for numerous differences in item characteristics, which exist even within the relatively homogeneous item categories on which we, following previous authors, focus. Brand name and organic certification are examples of these measures of item quality. In our sample we find that the upward impact on price from increased item quality has offset most of the downward impact of lower-priced outlets.

## 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.

In general, statistical agencies do not construct basic CPI indexes by averaging together prices drawn from different outlets. 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.

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 $i=1,\ldots, N$ is given by

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

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

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 weights $w_i$ attached to the different outlets. For convenience we also assume that the $w_i$ are share weights summing to unity.

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 $w_j^n$ that reflect purchasing patterns in a more recent period than do the weights for the units in the outgoing sample. Prices $P_j^n$ are the prices from the new outlet sample.

Then the change in the index between times 2 and 3 is defined by

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

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

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

and rearranging

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

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 log-mean prices charged by the two sets of outlets in time 2. The method used in the CPI implicitly subtracts the difference in average prices from the direct comparison measure. Only if that difference is zero will the two-period change be the difference in weighted averages, as was true in (1b).

Whether one views this as appropriate depends on one's views concerning the observed differences in prices across outlets. If consumers view outlets as equivalent except for the prices those outlets charge, then the first term in (4) would provide a better approximation than the CPI index to changes in the cost of living. Conversely, if prices in different outlets are considered equal on a quality-adjusted basis, then incorporating the second term in (4) is essential in order to avoid index bias.

Most discussions of new outlets bias have been concerned with the effects of trends in the market shares of outlet categories such as warehouse clubs or discount department stores. In this paper we examine the effects of changing market shares of outlet categories as well as of the changing market shares of outlets within outlet categories.

To distinguish those two 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 $W_k^n = \Sigma w_j^n$ for all outlets i and j in category k in the overlap time period 2. We also define $\overline{P}_k$ and $\overline{P}_k^n$ as the weighted average prices in outlet category k in period 2. The difference in outlet effects in (4) can be written as:

$$\sum_j w_j^n \ln\left(P_j^n\right) - \sum_i w_i \ln\left(P_i\right) = \sum_k W_k^n \ln\left(\overline{P}_k^n\right) - \sum_k W_k \ln\left(\overline{P}_k\right) \qquad (5a)$$

Rearranging,

$$\sum_k W_k^n \ln\left(\overline{P}_k^n\right) - \sum_k W_k \ln\left(\overline{P}_k\right) = \sum_k \frac{\ln(\overline{P}_k^n) + \ln(\overline{P}_k)}{2}\left[W_k^n - W_k\right] + \sum_k \frac{W_k^n + W_k}{2}\left[\ln(\overline{P}_k^n) - \ln(\overline{P}_k)\right]$$

(5b)

The first sum on the right-hand side measures the difference in prices due to the difference in expenditure shares of each category. That difference would be due to, for example, a greater expenditure share of discount department stores in the new sample. The second sum measures the difference in average prices within each category, including changes due to shifting consumption patterns. For example, changing shopping patterns within the category of large grocery stores would result in a change in average prices for the category. In Section VI we will adapt equations (5a) and (5b) to estimate within- and between-category effects on food prices in our samples.

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 the sets of outlets entering and leaving the sample will be represented by

[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).

identical items, even when their distributions of products sold are similar. This complicates the analysis of 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 or hours of operation, and so on. Intuitively, in a static equilibrium in which outlets offer different prices there must be exactly offsetting differences in outlet 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 outlets than at others, and whether there are trends in the average outlet-related premium or discount. 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.

White (2000) analyzed Canadian CPI indexes for 'other household equipment', non-prescribed medicines, and audio equipment for Ontario for 1990-1996. He showed that

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

those indexes had higher rates of inflation than alternative indexes based on either a unit value approach or one that explicitly calculates changes in the market shares of different outlet types. He also estimated the potential bias from using of an unrepresentative sample of outlets. Those two biases combined were estimated as between 0.2 and 0.4 percentage points per year for the Canadian CPI as a whole.

Unquestionably the most influential study of outlet bias in the CPI has been Marshall Reinsdorf's 1993 paper. After carefully reviewing the relevant theoretical and measurement considerations, Reinsdorf presented a comparison of prices in incoming and outgoing CPI rotation samples that is closely related to the method used in this paper. 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 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 0.24 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 0.05 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

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

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 how the growing SMC market penetration affects market-average prices, both directly and indirectly through the prices charged by 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 of household shopping choice to conclude that the compensating variation value to consumers of SMC 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 detailed CPI microdata on the 69 months from January 2002 through September 2007. 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 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 fruit and vegetable juices, our list roughly corresponds to 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 reducing heterogeneity 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 of goods sold by different outlet types. A

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

large grocery store might sell name-brand yellow bananas, while a discount department store might sell unbranded bananas.

Each of the categories in Table 1 represents a different “Entry-Level Item” or ELI, the ultimate sampling unit for items as defined by the BLS national office. ELIs comprise 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 (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] For example, in the bimonthly even metropolitan area of San Francisco-Oakland-San Jose, the ELI 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.

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

For our empirical analysis we constructed a sample of all item prices—what the BLS calls “quotes”— for each month from January 2002 through September 2007. For the 14 item categories above, this yields a total sample of about 360,000 price quotes in approximately 8,000 outlets. Note that the same individual item in a given store will be observed in multiple months until it rotates out of the sample or when it disappears from the shelves and the BLS data collector must substitute a similar item. CPI terminology refers to the substituted item as a new “version.” When such a substitution occurs in a store, the CPI analyst in Washington decides whether the new version’s characteristics are “comparable” or “non-comparable” to those of the old version. If the two versions are judged comparable, their prices are used in the index without adjustment, in the same way as if no substitution had taken place. If the versions are non-comparable, however, they are, in effect, treated as different products, and the difference in their prices is implicitly attributed to a difference in item quality (except for an inflation factor between

[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.

the two periods, which is imputed from the movements of other items in the sample).[11] For the purposes of this paper we will refer to the sequence of observations on a version as a "version string", and the sequence of observations on comparable versions of an individual product as a "quote string." Thus, a quote string may comprise more than one version string, and it may extend over a period from one month to several years, depending on when or if a non-comparable substitution takes place for that product. Our dataset for the 14 item categories contains about 18,000 quote strings.

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 appear), 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.

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 2007. 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 69 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 16 percent in January 2002 to about 25 percent in September 2007. The two SMC categories have exhibited the most striking growth. Discount Department Stores increased from 3.6 percent to 9.6 percent, and Warehouse Club stores from 3.1 percent to 6.1 percent. Among the three remaining categories, increases in the small shares of Convenience Stores and Small Grocery Stores more than offset a decline for Other Outlet Types.

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[11] Examples of the characteristics recorded by the CPI and used in comparability decisions are given in Section V below. Exceptions to the substitution-handling process described here, such as the use of hedonic regression for quality adjustment, are very rare in the CPI food categories.

The aggregate 15.7 percent share of SMCs in the last month of our data 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 calendar 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, 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. SMCs 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 statistically significant 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

For each of our 14 item categories, we estimate a semi-logarithmic regression model in which price is a function of both item characteristics and outlet effects, as well as time period. The individual observations in our data comprise the price, characteristics, and outlet codes of a given product version in a given month. As discussed above, a version string is observed in each month of our study period from the time it appears until it is rotated out of the CPI sample or its place is taken by a new version through forced item substitution. In any given month there may be more than one version string being observed within the same sample outlet. Because of the rolling pattern of CPI rotation, outlets and their associated version strings are entering and leaving our samples throughout the period of study.

Indicating a version string by the subscript *s* and its outlet by *j*, and using *t* to indicate month (the values of *t* run from 0 in January 2002 to 68 in September 2007), our model is

$$\ln P_{st} = \beta_0 + \pi_t^f + X_s\beta + \gamma_j + \varepsilon_{st} \qquad (6)$$

In (6) $\beta_0$ is an intercept term and the disturbance terms $\varepsilon_{st}$ are assumed to be independently and identically distributed for all *s* and *t*. Item characteristics are represented by a set of dummy variables $X_s$ specific to the version string, and $\beta$ is the associated vector of coefficients.[12] The term $\gamma_j$ is an outlet fixed effect for the *j*-th outlet, where *j* is, again, the outlet in which version *s* is sold. The values of $\pi_t^f$ are of particular interest because they comprise the price index implied by (6), with item characteristics and outlets held fixed. That is, for *t* running from 1 to 68, the values of $\pi_t^f$ are the estimated logarithms of the price level in period *t* relative to period 0 for a given set of item characteristics and in a specific outlet. We attach the superscript *f*, for fixed effects, to distinguish this price index from others we will present later in this section.

Although the item categories studied 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 characteristics of items sold at those outlets. For example, part of the difference in observed prices between categories might be explained by discount department stores selling items with different characteristics from those sold at large grocery stores. The item characteristics that we have available in the CPI data are included in the variables $X_s$ for each of our 14 item categories. 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. Here we employ dummy variables for virtually all non-write-in checklist categories for each ELI. If appropriate, we also include dummy variables coded from some of the write-in fields, such as H99. For example, the regression model for ham includes dummy variables for characteristics such as spiral cut and honey baked.

It is also important to note that the dependent variables in our regressions are measured on a per-unit basis, consistent with the general CPI practice for food items. For example, the dependent variables in the cola and butter regressions are the logarithms of price per ounce. Thus, variations in container 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.

We include a variable for the logarithm of size and its square to allow for those discounts.

We also include dummy variables for container size in $X_s$ whenever it is included in the ELI checklist specification, as in the cases of cola and juice. The use of size as a

[12] In estimating this model we ignore any differential correlations among the disturbance terms within and across quote strings in a given outlet.

characteristic is particularly important because larger sizes clearly are less attractive to consumers, *ceteris paribus*. If they were not, all outlets would be warehouse and club stores, which offer the lowest per unit price.

As noted above, we estimate the model in (6) separately for each of our 14 item categories. Consider the category of butter as one example. For butter, our sample contains 12,347 observations, corresponding to 503 version strings (465 quote strings) in 376 outlets observed over an average of 25 months per version string (27 months per quote string). Thus, there are 376 outlet fixed effects $\gamma_j$ in the butter regression, along with 68 dummy variables for months. The $X_s$ matrix includes, for example, a set of dummy variables representing whether the product is whipped as opposed to regular creamery butter, whether it is Grade AA or some other quality, and the weight of the item (8 ounces, 16 ounces, etc.). We also included two dummy variables for well-known national brands of butter.

We estimated this fixed effects model without weighting the observations. The resulting price index terms $\pi_t^f$ indicate wide variation within our sample period but little overall price change. The value for April 2003 is -.223, implying an approximately 20 percent price decrease from January 2002. The index then rises to a value of .185 in June 2004, or about 20 percent above the January 2002 level. By September 2007, however, the log-index has returned to .029, or about a three percent overall increase.

It is instructive to compare these index movements to those of an index derived using methods closer to those used in the CPI. For that we estimate

$$\ln P_{st} = \beta_0 + \pi_t^m + \delta_q + \varepsilon_{st} \tag{6a}$$

where $\delta_q$ is a dummy variable for the quote string of which version string $s$ is a component. Recall that the CPI treats prices within a quote string as comparable, but essentially treats any difference between the prices of different quote strings as due to product quality differences. Similarly, the price index terms $\pi_t^m$ effectively hold the quote string fixed, so that inflation is only estimated within each quote string. Consequently, we refer to $\pi_t^m$ as a matched model index, with a model corresponding to a quote string.[13] The distinction between our matched model and hedonic indexes is in the treatment of changes in item characteristics. When one item is substituted for another, the matched model index attributes the price difference to quality if there is a change in quote string, and to “pure price change” if there is no change in quote string—that is, if the CPI considered the new and old versions comparable. In calculation of the hedonic index $\pi_t^f$, the price difference is decomposed into quality and “pure price” differences based on the regression coefficients associated with the item characteristics that differ between the two versions. In any event, for butter, the price index in (6a) closely follows $\pi_t^f$: in April 2003 $\pi_t^m$ equals -.225, and it rises to .180 in June 2004 before falling to .017 in September 2007.

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[13] Since a quote string can comprise versions with slightly different characteristics, one could alternatively define a matched model index as one in which the model corresponds to a version string. We use our formulation because it corresponds to the approach used in the CPI.

We emphasize that our indexes $\pi_t^f$ and $\pi_t^m$ differ from the actual CPI for many reasons. Perhaps most importantly, our indexes are based on equally-weighted averages of logarithms of prices, whereas the CPI computes geometric mean indexes for each of 38 geographic areas using individual sampling weights for observations, then aggregates the area indexes using an arithmetic mean formula and expenditure weights taken from the Consumer Expenditure Survey. Nevertheless, the CPI index movements for butter are quite similar to those of our regression-based indexes. The CPI for butter fell 21 percent between January 2002 and April 2003, then rose by June 2004 to a level 19 percent higher than that in January 2002. For our study period as a whole, the CPI rose only 0.1 percent.[14]

We next turn to a consideration of our estimated outlet effects for butter. Because of the changing outlet mix in our CPI sample, we do not have a balanced sample: not all outlets appear in any given period. The $\gamma_j$ terms do not have to average to zero in each period. Rather, they are all measured relative to one arbitrarily chosen outlet whose $\gamma_j$ is set to zero. In Figure 3 we display the outlet effects in each period for 500 randomly chosen outlet-period combinations in our sample. (There are 11,798 such pairs in our butter sample, which if included would make the chart unreadable.) Also included is the simple linear trend estimated using those 500 data points. The figure shows the wide variation in fixed effects across outlets. It also shows a slight downward trend, which suggests that the outlets in the sample at the end of the study period tended to offer lower prices for butter *ceteris paribus*.

We can ask two questions about these outlet fixed effects, testing whether the trend displayed in Figure 3 is indicative of an actual market phenomenon. The first question is whether the $\gamma_j$ are significantly different from zero. Using a standard F test, the null hypothesis that all the outlet effects are zero is rejected with a very high confidence level. We therefore conclude that some outlets in our sample charge higher prices than others for butter products with the same measured characteristics. We will henceforth use the term "premium," which may be either positive or negative, to denote the fixed effect for a given outlet.

The second question we can ask about the fixed effects is whether there is a correlation between the outlet premiums and time. That is, does the average premium value change according to some linear, or non-linear, or even non-monotonic function of time? We address this question in two ways. First, we simply regress the average monthly average outlet premium against a time trend, as pictured in Figure 3. For butter, the coefficient of time is negative and highly significant, with a t-statistic of -6.72. Second, we apply a more general Hausman-type specification test. We can estimate equation (6) using a random effects rather than fixed effects specification of the $\gamma_j$ terms. If the random effects model is valid for our data, it offers a more efficient estimator of the outlet effects. However, the maintained assumption of the random effects model is that the $\gamma_j$ are uncorrelated with the other explanatory variables in the equation, including the dummies for time periods. Therefore, we apply a Hausman-type test of the null hypothesis that the outlet effects are independent of time. For butter, this null hypothesis can be rejected at

[14] There are no published CPI series at the detailed level of several of our item categories, and we make no attempt in this paper to compare the CPI to any of our estimated price indexes except that for butter.

the .0086 significance level.[15] Using either test, therefore, we conclude that the average level of the outlet premium for butter is not constant over time.

The CPI methodology implicitly assumes that differences in outlet premiums reflect differences in outlet quality as viewed by consumers, and that the price index should therefore be computed conditional on an average outlet premium level, as is done in the computation of $\pi_t^f$. If consumers are indifferent between outlets except for price, however, a change in the average outlet premium should be treated as a change in the price index. To represent the latter view, we define a third log-price index by setting $\pi_t^o$ in time *t* to equal $\pi_t^f$ plus the average outlet premium in the sample of price quotes in time t.

$$\pi_t^o = \pi_t^f + \left(\overline{\gamma_t} - \overline{\gamma_0}\right) \tag{7}$$

If the average premium is declining over time, as suggested by the trend in Figure 3, the index series $\pi^o$ will show a slower rate of inflation than $\pi^f$. This is what we observe for butter. As noted earlier, the value of $\pi_t^f$ in September 2007 is .029, or about a three percent increase after five years and eight months. By contrast, the ending value of $\pi_t^o$ is.010, indicating only a one percent increase.

Next, return to equation (6) and note that with dummy variables included in the regression for each month in our sample except the first, the average residual will be zero for each month.[16] Then, letting $\overline{\ln \hat{P}_t}$ be the average predicted value in period *t*, we can write

$$\begin{aligned} \overline{\ln \hat{P}_t} - \overline{\ln \hat{P}_0} &= \left(\overline{X_t} - \overline{X_0}\right)\beta + \pi_t^f + \left(\overline{\gamma_t} - \overline{\gamma_0}\right) \\ &= \left(\overline{X_t} - \overline{X_0}\right)\beta + \pi_t^o \end{aligned} \tag{8}$$

We now define a fourth price index $\pi_t^u$ obtained by regressing $\ln P_{st}$ on a set of time dummy variables alone, that is, equation (6) without the item characteristic variables or outlet fixed effects. The estimated values of $\pi_t^u$ will be the differences in mean log prices in each period relative to period *0*, and we have seen that these will equal the differences in mean predicted values on the left hand side of (8). The series $\pi^u$ would be an appropriate measure of price change under the assumption that consumers are

[15] To apply the test, we first estimated a random effects model of equation (6). This yields estimates of the component within- and between-outlet variances. Given these estimates, the random effects model can be equivalently estimated by subtracting from each regression variable its outlet-mean value multiplied by a term θ which is a function of the two variances and the sample size of the outlet. Our specification test was then an F test of whether, conditional on these θ-adjusted variables, we could accept the null hypothesis that the unadjusted differences of the time dummy variables from their outlet means significantly added to the explanatory value of the regression. Under the random effects model they should not.

[16] If this were not true for some time period t the sum of squared residuals could be reduced by a change in the estimated $\pi_t^f$.

indifferent between different outlets and that they also view the item category as perfectly homogeneous; they are indifferent among all the items represented.

The differences among $\pi^u$, $\pi^f$, and $\pi^o$, therefore, measure two components of change over time: an item characteristics component and an outlet premium component. Rewriting equation (7) gives the outlet premium component between periods *0* and *t* as

$$\pi_t^o - \pi_t^f = \left(\overline{\gamma_t} - \overline{\gamma_0}\right) \tag{9}$$

and the item characteristics component is given by

$$\pi_t^u - \pi_t^o = \left(\overline{X_t} - \overline{X_0}\right)\beta \tag{10}$$

Our alternative index results for butter and the other 13 item categories are shown in Table 2. The numbers in the table are estimated log-changes in price over the 69 months in our study period. The columns labeled U, F, O, and M contain the ending log-index levels for $\pi^u$, $\pi^f$, $\pi^o$, and $\pi^m$, respectively, and columns B through E display the index differences. As previously noted, for example, our hedonic index for butter ends the study period at a value of .029, and after adjustment by the average outlet effects we obtain an ending level of.010. For butter, the item characteristics component is in the same direction as the outlet component but is about three times as large (.055 compared to .018). The unadjusted index $\pi^u$, which does not hold the mix of item characteristics constant, ends at a level of -.045. In the case of butter, the most important changes in item characteristics implied a decreasing value to consumers: a decrease over time in the sample share of the top national brands, and the increased frequency of unusual weight values, such as three- or four-pound sizes. Adjusting for these changes raises the hedonic estimate of price change. Column E shows that the matched model index ends at a level 0.012 below the hedonic index. This implies that the matched model approach estimates about 1.2 percentage points more in quality change over the period than does the hedonic index.

The other rows of Table 2 highlight the widely varying rates of index change across our item categories, and the variation in the item characteristics component of index differences. The latter range from an approximate 7.8 percent decrease in item "quality"[17] for cola to more than an 7.5 percent increase for ham.[18] The item characteristics effect is positive, indicating declining "quality," in ten of 14 categories. Meanwhile, the estimates of the outlet effect cover a much narrower range and are negative in all but four item categories: apples, eggs, coffee and lettuce.

In the last row of the table we display weighted averages of the category results. The BLS does not construct consumer expenditure weights for all ELIs, and many of our categories comprise only part of an ELI; iceberg lettuce, for example, is only a small part

[17] As discussed in Section VII, we recognize that some aspects of what consumers view as item quality cannot be observed in our data. Also, some of the valuation of item characterstics, such as brand, may reflect market structure rather than quality per se.
[18] In the remainder of our discussion we treat "percent changes" and "log-changes" as synonyms, for reasons of expositional convenience.

of the Lettuce ELI. For this paper we used sample quote counts along with 2003-2004 CPI item stratum weights to yield rough estimates of the weights of our item categories in the CPI. Aggregating the category results using these weight estimates, we find that the average outlet component is -.0147. This implies that the effect of changing outlet mixes has had a negative effect on the price level for the 14 categories together of approximately 0.26 percent per year.[19] The negative sign is consistent with the hypothesis that SMCs or other new outlet types are offering lower prices to consumers, even after the characteristics of items sold in the stores are taken into account. In the next section of the paper we analyze the contributions of different outlet categories to this overall effect.

Perhaps surprisingly, the table also shows that the aggregate estimate of the item characteristic component is almost equal in magnitude but opposite in sign to the outlet component. Consequently, our aggregate movements in the hedonic and unadjusted price indexes are almost equal. Overall, our results imply an improvement in the quality of items sold of about 0.20 percent per year. As might be expected, large effects are in coffee and juice, which have numerous measured characteristics such as the flavor of juice or whether the coffee is decaffeinated. Relatively large effects are also observed, however, in such apparently homogeneous categories as eggs and fresh whole milk. One explanation is that package size is very important as an explanatory variable even in cases in which the individual product may seem very standardized aside from packaging. These results highlight the importance of examining differences in item characteristics across stores.

Equally surprising is the relationship between the matched model index $\pi^m$ and the other indexes. In principle, the matched model index should behave similarly to the hedonic index. Both do not include price changes occurring from outlet changes, and if analyst decisions about the comparability of new and old item versions are consistent with quality differences as reflected in the hedonic regressions then the matched model and hedonic indexes should approximate each other. In 12 of the 14 item categories, however, the matched model index indicates less inflation than the hedonic index. The implication is that either (i) the matched model approach is systematically mis-estimating the market value of quality differences, or (ii) there are unmeasured differences in product quality that are reflected in the matched model index but not taken into account by the hedonic regressions. Coincidentally, the differences shown in Column E of Table 2 lead the matched model index to be quite close to $\pi^o$, the quality adjusted price index that does not hold constant price changes due to outlet substitutions.

## VI. Decomposing Outlet Components by Outlet Category

We have shown in Figures 1 and 2 that the shares of discount store types have been growing rapidly in CPI food data. We have also shown in the previous section, using our fixed effects regressions, that the changing mix of outlets has had an overall negative

[19] For three item categories—ground beef, milk, and juice—our study period began shortly after January 2002 due to changes in their CPI checklist formats. All the estimates presented for those three categories were adjusted by imputing their price changes back to January 2002 from the indexes for the other categories..

impact on the price level in the categories we study. In this section we analyze the extent to which this negative impact has been due to the changing sample shares of SMCs and other store types.

Our discussion in Section II above illustrated one way of decomposing the impact of outlet mix on the price level, into the effect of the changing mix of outlet categories, on one hand, and the changing relative prices charged within each outlet category. Here we apply that approach to the individual outlet fixed effects, or premiums, that we estimated in Section V for each item category.

By dividing outlets into categories, we obtain an equation for the difference in average outlet premiums at the beginning and end of our sample period:

$$\bar{\gamma}_T - \bar{\gamma}_0 \equiv \sum_k w_{kT}\bar{\gamma}_{kT} - \sum_k w_{k0}\bar{\gamma}_{k0} \tag{11a}$$

With outlet premiums substituted for prices, equation (11a) corresponds to equation (5a) in Section II, where the categories *k* are our six store types: Large Grocery Stores; Discount Department Stores; Warehouse Clubs and Other Membership Retail Outlets; Small Grocery Stores; Convenience Stores; and Other Outlet Types. Periods *0* and *T* correspond to January 2002 and September 2007, respectively, and the terms $\bar{\gamma}_{kt}$ in (11a) are the mean outlet premiums for quotes in outlet category *k* in those two periods.[20] The terms *w* are the shares of quotes represented by each outlet category.

The use of outlet fixed effects in (11a) differs from the use of average prices in (5a) in two respects. First, the outlet fixed effects are explicitly drawn from samples in two different time periods rather than being drawn from two contemporaneous incoming and outgoing samples. However, the outlet fixed effects are estimated in an equation that includes dummy variables for the time periods, so the variation due to time has been purged from the outlet fixed effects. Second, differences in the average prices in the two samples in (5a) did not solely reflect differences in the outlets because of potential differences in item characteristics in the two samples. The outlet fixed effects do not suffer from this problem because they are derived from a regression that included dummy variables for item characteristics.

Again following our earlier equation (5b), equation (11a) can be rewritten as:

$$\bar{\gamma}_T - \bar{\gamma}_0 \equiv \sum_k \left(\bar{\gamma}_{kT} - \bar{\gamma}_{k0}\right)\bar{w}_{k\cdot} + \sum_k \left(w_{kT} - w_{k0}\right)\bar{\gamma}_{k\cdot} \tag{11b}$$

Finally, without changing the value of the right-hand side we can subtract from each term $\bar{\gamma}_{k\cdot}$ the overall mean outlet premium in the two periods $\bar{\gamma}_{\cdot\cdot}$, yielding

$$\bar{\gamma}_T - \bar{\gamma}_0 \equiv \sum_k \left(\bar{\gamma}_{kT} - \bar{\gamma}_{k0}\right)\bar{w}_{k\cdot} + \sum_k \left(w_{kT} - w_{k0}\right)\left(\bar{\gamma}_{k\cdot} - \bar{\gamma}_{\cdot\cdot}\right) \tag{11c}$$

The first summation is a set of within-category effects, weighted by the average of the period 0 and period T category weights. Each term in parentheses in this summation is

[20] Note that because the quotes and outlets in our sample change only slowly over time, we are not introducing volatility by defining the terms in (11a) for specific months rather than for longer time periods.

the change over time in the average outlet premium for the category.[21] For example, the mean outlet premium for the Large Grocery category could change because the mix of upscale and low-price grocery stores changed.[22]

The second summation in (11c) gives the between-category effects, the effects of the changing sample shares of the categories. Here these effects are weighted by the category's average outlet premium relative to the overall mean $\bar{\gamma}_{..}$ . Calculated in this way, an outlet category with an increasing sample share will add to the overall outlet component on the left hand side of (11c) if that category has a relatively high average outlet premium. If the category has a relatively low average outlet premium, an increase in its share will lower $\bar{\gamma}_T$ relative to $\bar{\gamma}_0$.

The results of our decomposition are shown in Table 3. The results for individual item categories were aggregated using estimated CPI weights as in Section V, and the total of -.0147 in Table 2 is the same value given in the last row of column C of Table 2. We can see that most of the total outlet component is explained by the between-category effects, the changes in category shares over time. About sixty percent of the between-category total, -.0060, is explained by the growth in the discount department store category, which as shown in the first row of Table 3 has a relatively low average outlet premium $\bar{\gamma}_{kt}$. That is, the growth in the share of discount department stores is estimated to lower aggregate prices by slightly more than 0.1 percent per year. Another contribution, -.0026 over our sample period, comes from the growth in the sample share of warehouses and club stores. These estimates of the direct impact of the growth in low-cost stores are qualitatively consistent with previous evidence and conventional wisdom. When we examine the item category data underlying Table 3, we find that the total between-outlet category effect is negative for 11 of our 14 items. More surprising than the between-category results is the relatively large within-category effect, notably the contribution of decreasing relative prices within the mix of Other Stores. This is a very heterogeneous group that differs widely from item category to item category, comprising such outlets as delicatessens, bakeries, and drug stores. Further study of the underlying trends within the Other group could be valuable.

## VII. Concluding Remarks

This paper confirms the potential importance of new outlets bias in the CPI. Using BLS-collected price data for 2002-2007, we observe a continuous increase in the market share of discount department stores and warehouse/club stores. We also observe significantly lower prices at discount department stores than at large grocery stores, even after adjusting for a large number of item characteristics. Similarly adjusted prices at

[21] As noted above, our regressions calculated outlet effects relative to an arbitrarily chosen outlet set to zero. For our decomposition exercise we adjusted the outlet effects so the mean over periods *0* and *T* would be zero in each category.

[22] It is important to distinguish our within-category effects from what Hausman and Leibtag called the "indirect effect" of SMC growth on the prices charged by regular supermarkets. If individual grocery stores lower prices in response to SMC entry, this will be picked up in our regression model by the price index terms $\pi$. Our within-category effect refers to the impact on the price level of outlet sample changes within a category.

warehouse/club stores are even lower. In 11 of 14 item categories examined, the increasing shares of lower-priced store categories reduced the average prices collected by the BLS. Changes in the distribution of outlets within categories also led to a substantial decline in average prices. Combined, changes in the distribution of outlets within and between categories lowered prices by about 1.5 percent over the 2002-2007 time period.

We also find a surprising degree of variation over time in the value of item characteristics. While the item categories might, at first glance, appear to contain relatively homogeneous goods, the average value of item characteristics has offset much of the decrease in average price due to the change in the distribution of outlets. Even items such as eggs and fresh whole milk have shown item quality increases of 5.5 percent and 3.7 percent, respectively.

The price variation accompanying that variation in characteristics leads to increases in the quality adjusted prices. The matched model index in this paper captures some, but not all of that increase. In 12 of the 14 item categories, the hedonic index increases faster than the matched model index.

The evidence described here by no means offers conclusive evidence of CPI bias. Most importantly, 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. Moreover, there may be differences in item characteristics across outlet types that are unobserved in the CPI data we employ. Some outlets may allow fruits and vegetables to lose freshness by remaining longer on the shelves, for example. Finally, we do not estimate and compare a model that reflects the precise current BLS procedures for calculating the CPI. Nevertheless, the fact that the market shares of SMCs are growing suggests that many consumers are benefiting from the lower prices at those stores.

We also know from our data that there are 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. Thus, our results suggest that outlet characteristics are not negligible factors.

# Appendix
# CPI Tomatoes Checklist

BUREAU OF LABOR STATISTICS **U.S. DEPARTMENT OF LABOR**

**CONSUMER PRICE INDEX - ELI CHECKLIST**

collection period: __ __ __ __   outlet number: __ __ __ __ __ __ __   quote code: __ __ __   arranging code: __ __ __ __

ELI No./title **FL031 TOMATOES**   cluster 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**
**Sample Shares by Outlet Type and Period**

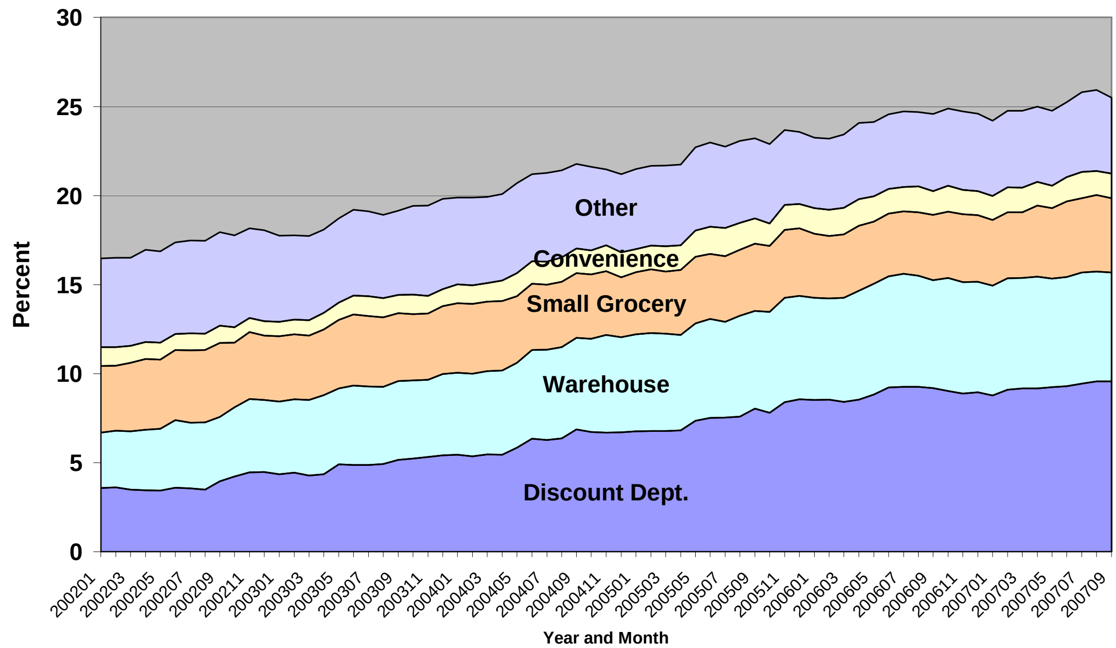


**Figure 2**
**SMC Sample Shares by Item Category, 2002 and 2007**

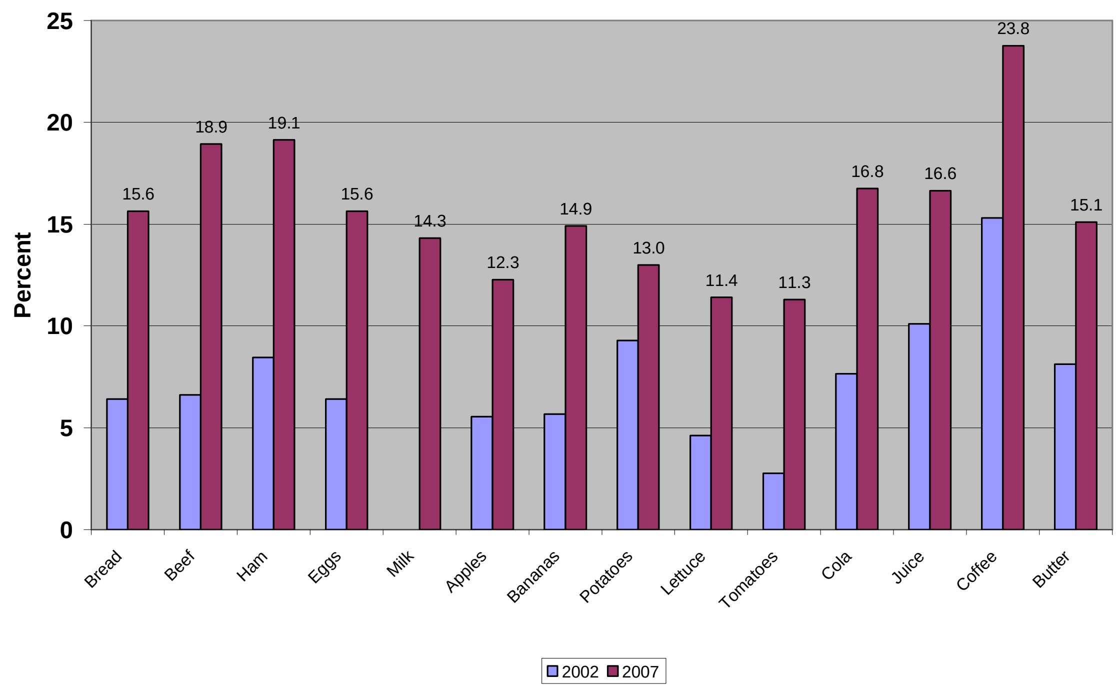

**Figure 3**
**Sample of Outlet Effects by Month for Butter**

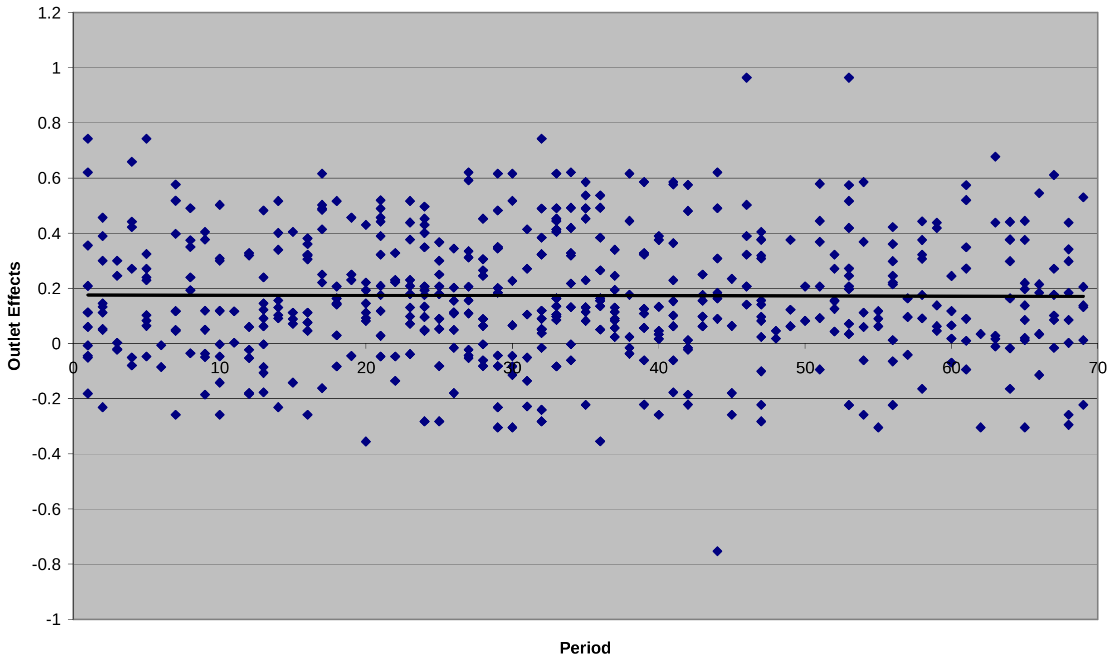

**Table 1. Item Categories**

| |
|---|
| White Bread |
| Yellow Bananas |
| Chicken Eggs |
| Ground Beef |
| Ham, Excluding Canned |
| Apples |
| Fresh Whole Milk |
| Potatoes |
| Tomatoes |
| Cola, National Brands |
| 100% Fruit or Vegetable Juices |
| Roasted Coffee |
| Butter |
| Iceberg Lettuce |

**Table 2. Alternative Indexes**
**Log-change Jan 2002-Sept 2007, By Item Category**

| Item Category A | Unadjusted Index U | Hedonic Index F | Hedonic Index Plus Average Outlet Premium O | Matched Model M |
|---|---|---|---|---|
| Apples | 0.297 | 0.324 | 0.329 | 0.321 |
| Bananas | -0.031 | 0.020 | -0.032 | 0.018 |
| Bread | 0.179 | 0.226 | 0.190 | 0.208 |
| Eggs | 0.582 | 0.484 | 0.527 | 0.472 |
| Ground Beef | 0.281 | 0.289 | 0.263 | 0.270 |
| Ham | 0.170 | 0.145 | 0.094 | 0.131 |
| Milk | 0.382 | 0.358 | 0.344 | 0.346 |
| Coffee | 0.304 | 0.219 | 0.237 | 0.234 |
| Juice | 0.237 | 0.179 | 0.173 | 0.137 |
| Potatoes | 0.212 | 0.189 | 0.168 | 0.193 |
| Butter | -0.045 | 0.029 | 0.010 | 0.017 |
| Lettuce | -0.057 | -0.077 | -0.076 | -0.083 |
| Cola | 0.108 | 0.187 | 0.185 | 0.166 |
| Tomatoes | 0.004 | 0.018 | 0.003 | 0.017 |
| **Weighted Average Across Items** | **0.2164** | **0.2196** | **0.2049** | **0.2055** |

| Item Category A | Difference between Hedonic and Unadjusted Indexes (U-F) B | Outlet Component (O-F) C | Item Characteristics Component (U-O) D | Difference between Hedonic and Matched Model Indexes (M-F) E | P values, Hausman test Random effects vs. Hedonic | P values, significance of time trend in explaining outlet effects |
|---|---|---|---|---|---|---|
| Apples | -0.027 | 0.005 | -0.032 | -0.003 | * | 0.0005 |
| Bananas | -0.052 | -0.053 | 0.001 | -0.003 | 0.0333 | * |
| Bread | -0.047 | -0.036 | -0.011 | -0.018 | 0.0885 | * |
| Eggs | 0.098 | 0.043 | 0.055 | -0.012 | 0.0016 | + |
| Ground Beef | -0.009 | -0.026 | 0.017 | -0.019 | 0.0114 | * |
| Ham | 0.025 | -0.051 | 0.075 | -0.015 | 0.1972 | * |
| Milk | 0.023 | -0.014 | 0.037 | -0.012 | 0.1186 | * |
| Coffee | 0.085 | 0.018 | 0.067 | 0.015 | 0.5146 | 0.7284 |
| Juice | 0.058 | -0.006 | 0.064 | -0.042 | 0.1302 | 0.2844 |
| Potatoes | 0.023 | -0.021 | 0.044 | 0.004 | 0.0846 | * |
| Butter | -0.073 | -0.018 | -0.055 | -0.012 | 0.0086 | * |
| Lettuce | 0.019 | 0.001 | 0.019 | -0.006 | 0.0004 | + 0.0002 |
| Cola | -0.080 | -0.002 | -0.078 | -0.021 | 0.0222 | * |
| Tomatoes | -0.014 | -0.014 | 0.001 | -0.001 | 0.0073 | 0.1513 |
| **Weighted Average Across Items** | **-0.0032** | **-0.0147** | **0.0115** | **-0.0141** | | |

* indicates p-value less than 0.0001. + indicates coefficient is positive.

**Table 3. Outlet Effects by Outlet Category, January 2002 to September 2007**
**Weighted Sample Average of Item Categories**

| | Large Grocery | Discount Dept. | Small Grocery | Conv. | Warehouse/ Club | Other | Total |
|---|---|---|---|---|---|---|---|
| Mean of average outlet premiums within category | 0.0173 | -0.1083 | -0.1009 | -0.0329 | 0.0012 | -0.0342 | 0.0000 |
| *Decomposition of Outlet Component:* | | | | | | | |
| Change in Average Outlet Premium Within Category | 0.0001 | 0.0007 | -0.0022 | 0.0002 | 0.0003 | -0.0041 | -0.0050 |
| Change in Weight of Category | -0.0015 | -0.0060 | 0.0001 | -0.0005 | -0.0026 | 0.0008 | -0.0097 |
| Total | -0.0014 | -0.0053 | -0.0021 | -0.0003 | -0.0023 | -0.0033 | -0.0147 |

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