Do the Poor Pay More Store-By-Store?

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Introduction

There is a long standing interest in the question of whether or not low income households face the same prices as households with higher incomes. If low income households face lower or higher prices than high income households, then income inequality may be greater or lesser than is suggested by simple comparisons of incomes.

A priori, an argument can be made for either case. Low income households may face higher prices if they are less mobile than other households and that difference reduces their ability search for stores with lower prices. They may also tend to shop at small, independent stores that cannot purchase wholesale goods in enough volume to receive volume discounts. In addition, higher crime rates may force local stores to pay greater insurance and security costs.

But low income households may have lower opportunity costs of search, allowing them to spend *more* time traveling to outlets with lower prices. Stores in low income areas may face lower wage costs. Finally, those stores may spend less on store maintenance and upkeep.

Interest in the topic developed after the unambiguously titled “The Poor Pay More: Consumer Practices of Low-Income Families” was published in 1963[1]. Among many studies of regrettable quality, a few academic and federal studies stand out. Summarized in Sexton (1971), those studies generally found either no difference in prices paid, or that the poor paid more for similar goods. Most of the studies examined specific cities, such as St. Louis or Detroit. Sexton summarizes two notable studies of Philadelphia. Dixon and McLaughlin (1968) examine the cost of 20 items in stores located in a low income inner city area of North Philadelphia and stores located in high income areas throughout the city. They concluded that the poor pay less for the same goods. Goodman (1968) found that 92% of low income families left the neighborhood during their principal shopping. He concludes that there is no evidence that the poor pay more for similar items.

That result rebuts an inference sometimes drawn from a BLS study conducted in 1966[2]. Examining the prices in 18 food items in high and low income areas of six cities, the study finds no evidence that chain stores charged higher prices in low income areas. But it did find that small independent stores charged higher prices and were more common in low income areas. Those results suggest that the poor might pay more if they shop near their residences. In a related study the Department of Agriculture also found no evidence that chain stores charged higher prices in low income areas. However, a Federal Trade Commission study of San Francisco and Washington, DC found that chain stores charged higher prices in low income areas.

Most of the more recent literature is summarized in Kaufman, et. al., (1997). Many of the studies either find no significant difference in prices, or find that the poor pay more.

[1] See Caplovitz (1963)
[2] See National Commission on Food Marketing (1966) Technical Report #10

The exception is Ambrose (1979), who finds that prices were lowest in small food stores in the inner city. Kaufman, et. al. remark that "[t]he findings on prices in small urban stores run counter to the strong findings of all other studies."

The Kaufman study also describes some areas of concern in any study of this topic. The main points that need to be addressed are: (1) selection of items; (2) choice of geographic areas; (3) choice of stores in geographic areas; (4) the method of averaging prices over items and across stores, and (5) how to treat missing items.

Their points may be summarized as follows: The selection of items in each store must be similar so that researchers are not literally comparing apples and oranges. More importantly, the items must be of similar quality to avoid mistakenly inferring that low income households pay less when they are simply purchasing lower quality items. The choice of geographic area is important for studies that assume that households shop in nearby outlets. In particular, many low income households do not live in 'low-income' areas, so that prices in low-income areas may not reflect prices faced by many low-income households. The choice of stores is important because low income households appear to shop more frequently at independent stores, rather than chain stores. Studying a sample of chain stores would then provide an unrepresentative picture of the shopping experience of low-income households. The method of averaging prices across outlets and items is important because some outlets are more frequently patronized than others, and some items are more frequently purchased than others. If possible, prices should be weighted by expenditures or sales volume. Missing values may be a problem in small samples, requiring authors to carefully consider how the values might be imputed.

Recently, two papers have found that the poor pay less. Hayes (2000) examines individual prices collected for use in the Consumer Price Index (CPI). Using data from 1998, she tests for the difference across zip codes in average prices for a set of relatively homogeneous items—whole chickens, eggs, milk, bananas, oranges and lettuce.[3] Zip codes are defined as being poor or not with several different measures. She finds no evidence that average prices in poor zip codes are higher than other zip codes. In fact, she typically finds that 2 of 5 items have prices that are statistically significantly lower. Overall, prices in poor zip codes are up to 6 percent lower than prices in affluent zip codes.

Aguiar and Hurst (forthcoming) use A.C Nielsen Homescan data covering purchases in Denver from January 1993 through March 1995. The Homescan survey contains data such as prices, UPCs and outlet names, for items purchased by families volunteering to enter the Homescan panel. Volunteers also answer a multiple-choice question about their income. Differences in quality can be identified with the UPC code. Their sample relies heavily on chain stores; 85 percent of grocery stores purchases were made at outlets of four chain stores. Although the authors do not provide information about specific items, they conclude that the prices paid by high income households are 2.1 percent higher on average than those paid for low income households.

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[3] Her sample is limited to nonkosher, broiler/fryer whole chickens; a dozen large grade A white eggs; loose navel oranges; and individually packaged iceberg lettuce

In this paper we use data from the Telephone Point of Purchase Survey (TPOPS), previously unused for this subject, which collects information about household expenditures at outlets they patronize. The BLS uses the survey to create a frame of outlets from which it collects prices. In 2001, respondents were also asked a question about their income. Combining data from that survey with price data from the CPI Research Database (RDB), we compare prices charged at outlets patronized by families in each of three income categories, and calculate differences in expenditure weighted average prices. We also use detailed information in the RDB about the characteristics of each item being priced to adjust for possible differences in the quality of items sold.

This allows us to control for many of the problems with the previous literature. First, we avoid the problem of defining "poor" stores or "poor" neighborhoods, because we have exact data on how much consumers spend at various outlets – we know where they shop. Second, the detailed data on goods characteristics allows us to compare control for all prices determinants of the goods, meaning we effectively compare prices the same goods. Therefore, lower prices paid by low income families do not represent lower quality goods. In addition, the expenditure data allows us to avoid taking simple averages of prices across stores.

Unlike Aguiar and Hurst (forthcoming), the data we use spans many years and they are recent. It avoids possible accuracy issues with Homescan, such as small sample sizes for the poor. We are also able to look at areas all over the country, instead of just Denver, and in fact control for differences in average prices across areas. However, because we do not observe what families buy at a given store, we can only measure price differences between stores. We cannot measure average price differences due to more or less intense shopping for sales or bargains within a store.

Overall, we find that the poor pay neither more nor less than the rich at the stores they shop at. This varies by good – for some goods the poor pay more, some less, but for most items there is no discernable difference. The differences by good could be due to sampling variation.

Data

Established in 1997, the TPOPS is a quarterly survey of households (or more correctly, consumer units) used to create a frame of outlets from which the BLS may collect prices. In that survey households report their spending on specific goods and services in every outlet they patronized. Telephone numbers are selected at random. The consumer units that are called are intended to be in the survey for four consecutive quarters. Every commodity and service belongs to one of 16 groups. For each geographic area (the Primary Sampling Unit, or PSU) one group is selected and all households in that PSU are asked about their expenditures in that group. In each new quarter a new group is assigned to a PSU, so that households which stay in the survey for the full four quarters report expenditures for four different groups.

In 2001 only, consumer units new in the survey were asked to place their incomes into one of the following three income groups, where CUSIZE is the number of people in the consumer unit:

1 Lower
less than $8,000 for CUSIZE < 2; less than $18,000 for CUSIZE = 2;
less than $18,000 for CUSIZE = 3; less than $24,000 for CUSIZE > 3

2 Middle
$8,000-$30,000 for CUSIZE < 2; $18,000-$57,000 for CUSIZE = 2;
$18,000-$64,000 for CUSIZE = 3; $24,000-$66,000 for CUSIZE > 3

3 Upper
greater than $30,000 for CUSIZE < 2; greater than $57,000 for CUSIZE = 2;
greater than $64,000 for CUSIZE = 3; greater than $66,000 for CUSIZE > 3

The proportions are roughly 15% for group 1 (poor), 50% for group 2 (middle), and 35% for group 3 (upper), which roughly match the proportions in 2001 March Current Population Survey.

Because only consumer units meant to be in the first of four quarters in the survey were asked the income question (not those replacing units that left the survey), and due to a response rate of about 80% of those asked and an attrition rate of about 17% after each quarter, most units cannot be assigned an income group. Because units stay in the survey for up to four quarters, the number of units that can be assigned an income group rises from about 20% in Q1 2001 to about 55% in Q4 2001 before falling in Q3 2002.
The CPI RDB contains all price quotes obtained by the BLS for all commodities and services, excluding housing, monthly from 1987 to the present. The data we use is from May 2002 to April 2007. Because new outlets are chosen in each PSU for each POPS category every four years, each good is in the database for at most four years.

The BLS categorizes goods as follows. One or more checklists make up an ELI (entry level item), which are then grouped into POPS categories. Each checklist is a set a goods characteristics that serve to (1) list all characteristics that need to be disaggregated, in order to select an exact good to price, and (2) aid in choosing a comparable substitute if the good selected should no longer be available. Each characteristic variable on the checklist is called a spec. For example, if one checklist item is serving size, large or small, a size will be decided on based on the revenue share in that store for large or small versions of that good. Then the next checklist item, such as flavor, will be selected on, until eventually a large, strawberry, organic, low-fat, etc. item is chosen, which should have no further price variation within those characteristics. Therefore, these checklist items list all characteristics that matter for a good's price, as well as some that don't. (Footnote: some checklist items are catchall categories, such as other, misc., etc., and are listed as a "99" field).

The BLS chooses the outlets to visit by first deciding how many quotes to get for each ELI, and then randomly selecting the outlet to price it at with the probability of selection being equal to that outlet's share of all expenditure for the POPS group that the ELI is part of.[4] When the outlet is visited for the first time, the exact goods to be priced are chosen randomly in several stages. At each stage the probability of selection equals the revenue share as reported by the outlet. This process is called disaggregation. After a good is chosen to be priced, it is repriced every month for four years until a new TPOPS is conducted which begins the selection again, or until that good is discontinued. Our study is necessarily limited by the fact that the disaggregation occurs separately from the TPOPS. Consequently, while we observe the prices charged by outlets patronized by families in each income group, we do not observe the actual prices paid by those families.

Methodology

We calculate average prices for specific goods for each income group. Because of the sampling process, an unweighted average implicitly weights each price quote by total expenditures at the given outlet. We re-weight prices so that the average reflects the expenditures by income group at that outlet. The new average price is what the average price level would have been if only that income group had been included in the TPOPS survey. This re-weighting is needed because the price quotes have already been chosen based on probabilities from all income groups combined.

Let 1_{it} denote an indicator function for whether good i was chosen for pricing at time t. The probability of a particular good i being chosen in period t, $pr_t(i)$, at outlet o is given by:

$$E(1_{it}) = pr_t(i) = \frac{e_o}{\sum_o e_o} = \frac{\sum_I e_{o,I}}{\sum_o \sum_I e_{o,I}}$$

where e_o is total expenditures on outlet o and $e_{o.I}$ is the expenditures by income group I on outlet O. The estimate of the expenditure share weighted average price, $\bar{p}_t$, taken across price quotes, p_{it}, for specific good i in period t is:

$$\sum_I 1_{it}\, p_{it} = \dot{\hat{\bar{p}}}_t$$

We calculate an adjustment factor for each outlet o and income group I

[4] Various weights are used to compensate for the imperfect match between ELIs, POPS categories, and item stratum, but as the total effects of these are small, we ignore them here.

$$\frac{\dfrac{e_{o,I}}{\sum_o e_{o,I}}}{\dfrac{\sum_I e_{o,I}}{\sum_o \sum_I e_{o,I}}} = A_{o,I} \quad .$$

We multiply each price quote by this adjustment factor in order to yield an implicit weight equal in expected value to the probability of selection for that income group. Let $\hat{\bar{p}}_{It}$ denote the estimated average price for income group I.

$$\hat{\bar{p}}_{It} = \sum_i 1_{it} A_{o,I} p_{it}$$

The expected value of $\hat{\bar{p}}_{It}$ is

$$E(\hat{\bar{p}}_{It}) = E(\sum_i 1_{it} A_{o,I} p_{it}) = \sum_i E(1_{it}) A_{oI} P_{it}$$

$$= \sum_i \frac{e_o}{\sum_o e_o} \frac{\dfrac{e_{o,I}}{\sum_o e_{o,I}}}{\dfrac{\sum_I e_{o,I}}{\sum_o \sum_I e_{o,I}}} p_{it} = \sum_i \frac{e_{o,I}}{\sum_o e_{o,I}} p_{it} \quad ,$$

which is the expenditure share weighted average price if only members if income group I were in the BLS sample. For a specific good this is taking the average price of that good across different outlets weighted by that income groups' expenditure at those outlets.

Those averages may also be obtained through weighted least squares. To estimate averages with weighted least squares, we create a separate observation for each income group for each price quote. Each of these three observations differs only in the weight it is given, which is the adjustment factor A_{oI}, and the values of dummy variables for income. Regressing price on just those dummy variables would estimate coefficients equal to the average price in outlets patronized by each income group, using weights A_{oI}. Regressing price on an intercept and dummy variables for medium and high incomes would estimate coefficients equal to the difference between prices at medium income and low income stores and the difference between price at high income and low income stores.

However, using regression analysis allows us to use dummy variables to control for regional effects, general inflation over time, and variation in the quality of goods. We therefore create dummy variables for publication region and all of the important characteristics described on the BLS checklists. When possible we also create dummy variables for many of the written characteristics, such as brand.

Because the monthly price for any given good is subject to serial correlation, we take the average price for a particular good chosen from dissagregation over all months it is priced as one observation. A dummy variable is created to indicate the middle period for which the good was priced, in order to control for general inflation.

We perform two types of analyses. In the first, we use the characteristic variables to select a unique item that can be priced in many areas and time periods. For example, apples are limited to red delicious, not organic, loose (not in a bag), not wax-free nor pesticide-free apples.

Because every observation of the good should be exactly the same, price variation across income groups cannot be attributed to quality differences.

The list of goods includes one example from each checklist used in the combined regressions described below. Let β_i and D_i denote the coefficient and dummy variables, where i can be H for high income, M for medium income, t represents the period that a particular quote centers on, a represents the area, and s represents checklist variables. For each homogenous good, a weighted regression is estimated using the following equation:

$$\ln p_{it} = \beta_H D_H + \beta_M D_M + \sum_t \beta_t D_t + \sum_a \beta_a D_a + \varepsilon_{it}$$

where ε_{it} is an error term. In this model the coefficients on the income group dummies, β_H and β_M, are the percentage differences between that income group's average prices and those faced by low income households.

In our second analysis we do not attempt to identify an unique item. Instead we use the characteristic variables to account for price variation due to differences in quality:

$$\ln p_{it} = \beta_H D_H + \beta_M D_M + \sum_t \beta_t D_t + \sum_a \beta_a D_a + \sum_s \beta_s D_s + \varepsilon_{it}$$

To minimize the chance that quality variation explains the variation in prices, we include dummy variables for all of the characteristics and all variations of the '99' fields. Two spellings of a brand name would therefore be assigned two different dummy variables. The income group coefficients in these regressions are effectively weighted averages of the coefficients that would have been obtain if separate 'homogenous' regressions were estimated for every checklist good included.

Results

The results for our list of 27 homogenous goods are presented in table 1 below. The signs of the coefficients are mixed.[5] For the high income variable, one is negative and significant, meaning the high income households pay less than low income households, and four are positive and significant, meaning high income households pay more. For the medium income group, one is negative and significant and one is positive. The results for the regressions using characteristic variables are presented in table 2. One is negative and significant and two are positive and significant for the high income group, while for the medium group they are four and three respectively. In the majority of cases for both medium and high income groups, prices are not statistically significant different than prices offered by low income stores.

The results are consistent with the true difference being zero for all groups and goods, with the coefficient variation arising from sampling variation. In other words, if there was no difference in average prices between high income and low income stores, sampling variation would lead to a two tailed distribution of coefficient results, the result would some positive, some negative, but most insignificant.

Conclusion

Table 5 summarizes our preliminary results. We do not find strong evidence that high or low income households shop at outlets charging different prices. This is consistent with the findings of Aguiar & Hurst (forthcoming). They find that for roughly similar income groups to our own, high income households pay 2.1% more than low income households, which is a very small difference. Our data only allows us to look at across store variation in prices, not whether different income groups pay differently at the same stores, perhaps because they shop more or less intensely for bargains. Thus we would find less than a 2.1% difference, which is difficult to statistically detect.

[5] Some coefficients are very small, especially for table 1, and the standard errors are small enough to be reported as zero. Because these coefficients are so small, we count them similar to statistically insignificant coefficients.

Table 1: Homogeneous goods

Panel A

Standard errors below coefficients

Item	Med	High	N	adj. R^2
Apples	0.01021	-0.04771	170	0.591
	0.03891	0.04999	170	
Bacon	0.02343	0.05821	1158	0.456
	0.01819	0.02776	1158	
Bananas	0.06380	0.07590	222	0.734
	0.02301	0.02908	222	
Beef	0.00390	0.07505	2398	0.444
	0.00839	0.01280	2398	
Bread	-0.01748	0.05953	871	0.457
	0.02369	0.02486	871	
Butter	0.00000	0.00000	14	1.000
	0.00000	0.00000	14	
Catsup	0.00000	0.00000	14	1.000
	0.00000	0.00000	14	
Chicken	0.00000	0.00000	14	1.000
	0.00000	0.00000	14	
Chops	-0.03289	-0.03159	2995	0.433
	0.01062	0.01357	2995	
Coffee	0.00000	0.00000	21	1.000
	0.00000	0.00000	21	
Eggs	-0.03910	-0.01941	57	0.898
	0.05649	0.06301	57	
Fish	0.00000	0.00000	20	1.000
	0.00000	0.00000	20	
Flour	-0.01184	0.01943	57	0.865
	0.03212	0.05112	57	
Franks	0.02108	0.00875	415	0.532
	0.01991	0.02357	415	

Table 1: Homogeneous goods
Panel B
Standard errors below coefficients

Item	Med	High	N	adj. R^2
Green Beans	0.00000	0.00000	15	1.000
	0.00000	0.00000	15	
Lettuce	-0.01343	-0.00249	320	0.395
	0.03874	0.05733	320	
Margarine	0.00000	0.00000	12	1.000
	0.00000	0.00000	12	
Whole Milk	0.01200	0.03159	109	0.791
	0.02770	0.04324	109	
Low Fat Milk	0.00000	0.00000	26	1.000
	0.00000	0.00000	26	
Peanut Butter	-0.02381	0.02398	25	0.947
	0.03656	0.04296	25	
Potatoes	0.01089	-0.09449	56	0.999
	0.06789	0.11184	56	
Soda A	0.00000	0.00000	73	0.772
	0.00442	0.00622	73	
Soda B	0.05441	-0.00090	11	1.000
	0.03079	0.04401	11	
Soup	0.00000	0.00000	19	1.000
	0.00000	0.00000	19	
Sugar	0.00000	0.00000	3	
	0.00000	0.00000	3	
Tea	0.00000	0.00000	12	1.000
			12	
Tuna	0.00000	0.00000	15	1.000
	0.00000	0.00000	15	

Table 2: Characteristic variables included in regression
Panel A
Standard errors below coefficients

Item	Med	High	N	adj. R^2
Apples	-0.05615	-0.02802	1040	0.503
	0.01729	0.02195	1040	
Bacon	0.00551	-0.00260	14077	0.798
	0.00471	0.00643	14077	
Bananas	0.02711	0.03679	661	0.597
	0.01637	0.02102	661	
Beef	0.02995	0.02366	28450	0.666
	0.00310	0.00439	28450	
Bread	0.01192	0.02782	14484	0.954
	0.00467	0.00608	14484	
Butter	0.00319	-0.00001	228	0.883
	0.00769	0.00894	228	
Catsup	0.00000	0.00000	96	0.739
	0.00000	0.00000	96	
Chicken	-0.01455	-0.00694	837	0.888
	0.01642	0.02274	837	
Chops	0.01353	-0.02889	21509	0.422
	0.00472	0.00620	21509	
Coffee	0.00051	-0.00105	487	0.933
	0.00332	0.00420	487	
Eggs	0.00000	0.00000	544	0.838
	0.00645	0.00836	544	
Fish	-0.00602	-0.03099	434	0.883
	0.01203	0.01817	434	
Flour	-0.00371	-0.00169	425	0.809
	0.00801	0.01079	425	
Franks	-0.05615	-0.02802	5734	0.903
	0.01729	0.02195	5734	

Table 2: Characteristic variables included in regression
Panel B
Standard errors below coefficients

Item	Med	High	N	adj. R^2
Gas	0.00105	0.00424	117	0.976
	0.00331	0.00530	117	
Green Beans	-0.00079	0.00208	74	0.828
	0.00359	0.00470	74	
Lettuce	-0.00431	0.00705	907	0.805
	0.01125	0.01607	907	
Margarine	0.00034	-0.00092	287	0.887
	0.00437	0.00582	287	
Whole Milk	-0.02810	-0.02881	392	0.916
	0.01338	0.01804	392	
Low Fat Milk	-0.00365	-0.01821	379	0.948
	0.01140	0.01604	379	
Peanut Butter	0.00000	0.00000	158	0.808
	0.00000	0.00000	158	
Potatoes	0.02995	0.02366	953	0.768
	0.00310	0.00439	953	
Soda	-0.02075	-0.00969	537	0.803
	0.01595	0.01950	537	
Soup	-0.00715	-0.01079	470	0.925
	0.00515	0.00651	470	
Sugar	-0.05401	-0.00641	141	0.989
	0.02738	0.03752	141	
Tea	-0.01710	-0.00098	426	0.985
	0.00827	0.00946	426	
Tuna	0.01606	-0.00415	117	0.932
	0.02642	0.03840	117	

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