The Welfare Implications of Rising Price Dispersion*

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Abstract

Over recent decades there has been a considerable rise in US income inequality as measured by official statistics. The measures of inequality typically used are based on price indexes for a representative US consumer. The representative consumer assumption is not crucial in a world with a stationary relative price distribution or with an identical basket of goods consumed by different income groups. However, using household data on non-durable consumption between 1994 and 2005, we document that the relative prices of low-quality products that are consumed disproportionately by low-income consumers were falling over this period. This means that much of the rise of measured income inequality has been offset by a relative decline in the prices of products that poorer consumers buy. By relaxing the standard assumptions underlying the representative agent framework we find that non-durable inflation for consumers in the 10th percentile of the income distribution has been 7.3 percent lower than inflation for the 90th percentile over this period (or 0.6% per annum). This implies that around half of the increase in conventional inequality measures during 1994 – 2005 is the result of using the same price index for non-durable goods across different income groups. Moreover, we provide evidence that the pattern of rising price dispersion is not confined to our sample of non-durable goods or to the recent period, and thus the overstatement of "real" inequality in official statistics is likely to be larger.

I. Introduction

According to the US Census, inequality has risen substantially over the last few decades. Real income for the poorest decile of the income distribution grew by just 13 percent from 1973 to 2006, or less than 0.4 percent per annum (Figure 1) [1]. High-income households have fared somewhat better, with real household income at the 90th percentile rising by 41 percent in this period or 1.0 percent annually. These facts have led to an active area of inquiry into how the fruits of economic progress are distributed (see Goldin and Katz (2007) for a recent survey). But while the rise in US inequality has become "conventional wisdom", little attention has been paid to the fact that the standard measures of inequality *assume* that all American consumers buy the exact same basket of goods and face identical prices. In this paper we focus on the fact that "real" income or welfare does not only depend on the dollars in consumers' pay checks, it also crucially depends on what consumers can buy with those dollars. We relax the standard assumption of a representative agent underlying the calculation of conventional price indexes and re-examine the evidence on US real income growth and inequality.

Using scanner data on household consumption of non-durable goods between 1994 and 2005, we document that the relative prices of low-quality products that are consumed disproportionately by low-income households were falling over this period. This implies that non-durable inflation for the 10th percentile of the income distribution has only been 4.3 percent between 1994 and 2005 (0.4 percent per annum), while the non-durable inflation for the 90th percentile has been 11.9 percent (1.0 percent annually), and 13.4 percent (1.2 percent annually) for the richest 5 percent of households in the sample. Over the period 1994 – 2005, the conventionally measured ratio between real household income at the 90th and 10th percentile rose by 5.7 percent (0.5 percent per annum) and the $95^{th}/10^{th}$ ratio rose by 7.5 percent (0.7 percent per annum). This suggests that the inflation differential in non-durable goods (around 30 percent of total consumption) is enough to offset almost 40 percent of the rise in both of these inequality ratios over this period. In the case of other common inequality measures, the $80/20^{th}$ and $95/20^{th}$ income ratios, the non-durable inflation differential is enough to offset over 80 percent and 50 percent, respectively, of the rise in these indicators. Moreover, we provide evidence that suggests that the increase in price dispersion is not limited to the products in our sample nor to our time

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period. If differences in income-group specific inflation rates in our sample are representative of the broader economy, then real income growth in the US has been much more substantial and equal than suggested by standard measures. In that case, "real" inequality may have actually *fallen* between 1994 and 2005.

Figure 2 illustrates the importance of understanding the impact that changing relative prices have on the mapping between real income and welfare. For simplicity assume that consumers choose between goods X or Y, and that the non-homothetic utility function is represented by indifference curves IC1, IC2 and IC3. These indifference curves get steeper as you move out from the origin, with the natural interpretation that good X is a higher quality good. At initial relative prices Px/Py rich households prefer to consume good X (point H1 on IC3 in the figure) and the poor prefer to consume good Y (point L1 on IC1 in the figure). Under these initial conditions, a fall in the price of good Y (the good consumed by the poor) to Py', as depicted by the dotted budget constraints, increases the income of both rich and poor (in terms of good Y), but only raises the welfare of the poor. After the change in prices, the poor settle at L2 in the figure on a higher indifference curve IC2, while it is optimal for the rich to remain at point H1. We believe this figure captures the essence of our empirical findings, where relative price changes that favor the poor increases their relative welfare without being captured by official statistics.

As suggested by Figure 2, the reason behind the fall in the gap of "real" income or welfare between rich and poor is a fall in the relative price of goods consumed by the poor. Conceptually this change in relative prices can arise either because the price of "existing" goods (i.e., goods consumed throughout the entire period) has changed, or because of the introduction of new goods that are not consumed by all households. We show that the introduction of new goods over this period has benefitted each group substantially but relatively equally. If we define new goods as any product that was not consumed in 1994 but was consumed by at least one household in 2005, then the rich have benefitted slightly more by the introduction of new goods, as prices have fallen 1.4 percent (0.1 per annum) more than for the poor due to new goods. The results are similar when we define new goods specifically to the geographic area in which households shop, implicitly acknowledging that there is geographical segmentation in retail markets (this calculation can currently only be performed for the food sample). Overall, this suggests our results are driven primarily by the change in relative prices of existing goods.

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While most of the existing studies on the evolution and distribution of the economic growth have focused on "income" rather than "price" measurement, several papers have highlighted the importance of correctly measuring prices. Two recent studies have assessed the impact of immigration on prices (Lach (2007) and Cortes (2008)). Cortes (2008) quantifies the downward pressure on immigrant-intensive services of an increase in the share of low-skilled immigrants in the labor force, and emphasize the importance of taking into account the "price" effect when assessing the impact of immigration on the native population. The BLS has a tradition of computing group-specific inflation series (e.g., Garner et al (1996) and Cage et al (2002), and similarly Hobjin and Lagakos (2005)). But the shortcoming of these studies is that they do not use pricing data specific to each income group, but rather allow the shares of expenditures in different product categories to vary by income group. As we show in the main text, almost all of the results in our paper come from within-product category changes in prices (Maxwell vs Illy coffee), rather than the relative price changes between product groups (coffee vs soda), and so are missed by papers that use coarser price data. A recent study by Moretti (2009) suggests that college graduates have experienced relatively larger increases in the cost-of-living because they have concentrated in metropolitan areas characterized by a rising housing costs.

II. Data Description

II. A. Overview

The paper uses detailed household consumption data on a large set of mostly non-durable products sold in grocery, drug, mass merchandise, and other stores. The data is part of the Homescan database, collected by ACNielsen in the United States, that records prices and quantities of the purchases of thousands of households. ACNielsen provides Universal Product Code (UPC or barcode) scanners to a demographically representative sample of households. Households then scan in every purchase they make. We use two extracts of the complete Homescan database that provides us with a vast array of goods with barcodes. Moreover, we have detailed information on the characteristics of the households making the purchases.

We refer to the first extract of the Homescan data as our "Non-Durable" database. For this extract we have price and quantity data for every UPC purchased by a sample of 41,500 households for every quarter in 1994, and 55,000 households every quarter between 1999:Q1

and 2003:Q4. In addition, we have household-level information on every UPC purchase of a sample of 3500 households in 2003:Q4, together with detailed household characteristics. Table 1A summarizes this database in terms of the number of households, number of UPCs and "modules" (ACNielsen's classification of different UPCs into broader product categories). Examples of non-food modules included in this database include "cosmetics", "toys and sporting goods", "houseware appliances", "cookware", and "wrapping materials and bags".

The second extract we use includes detailed information on the food purchases and demographic characteristics of a large subsample of households included in the Homescan database between 1998 and 2005. We refer to this extract as the "Food" database. In this extract, we have household level data on every purchase in all food modules. Examples of food modules are "soft drinks non-carbonated", "sugar, sweeteners", "seafood" and "prepared, ready to eat food". Table 1B provides summary statistics of the number of UPCs, modules and households included in this database. The data is divided into four broad categories: dairy, dry grocery, frozen and processed foods, and random weight products. We obtained detailed household information on approximately 8,000 households from 1998 to 2003, and around 38,000 for 2004 and 2005. In 2005 this extract includes 640 modules and over 380,000 UPCs, most of which are classified under the dry grocery category. As we explain in the next section, we combine the information from both Homescan extracts to compute income-specific price indices over time.

A number of characteristics of the household are included in this database. In particular, household income, the head of household's occupation and education level, and household size are included. The distribution of households by income group and household head education level are provided in Figures 3A and 3B. Since we rely heavily on the information of households that are among the poorest and richest in our data, it is useful to examine how well our data represents the true population. According to the US Census Bureau the cutoffs for the 10th and 20th percentile income distribution are approximately $12,000 and $20,000, respectively.[2] Around 8 percent of our sample of households falls below the $15,000 threshold, and around 14 percent of the households have income less than $20,000. The cutoff for the 80th percentile is approximately $97,000. Around 10 percent of our sample has income over $100,000. This

implies that in 2005 we have detailed data on over 5,000 households that are in the lowest deciles of the income distribution and almost 4,000 households in the upper deciles.[3,4]

These data are ideal for understanding how prices evolve for households in different income groups. First, they include a long time series of price and quantity data for a large sample of non-durable consumption goods consumed by each income group. This is an advantage relative to current studies that do not observe the specific prices that households pay for each item. Our data circumvents these limitations by using data directly collected by a representative set of households. Second, we can identify the different goods purchased by each income group down to the barcode level. While official statistics are based on the basket of a representative agent, these data allow us to measure the differences in consumption baskets across income groups. This information is not observed by the BLS or other statistical agencies. A third crucial characteristic of these data is that along with prices of each product, quantities of the identical products are collected at the same frequency. Therefore we observe expenditure weights by income group. In short, the data is ideal to examine income-group specific price indexes.

II. B. Stylized Facts on Consumption Baskets by Income Group

In this section we use Homescan data to document three key facts that highlight the differences in the pattern of consumption across different income groups. First, the basket of non-durable goods consumed differs systematically by income group – the poor consume lower quality products than the rich. Second, the poor consume fewer varieties of goods (fewer UPCs), and this gap with the rich has been widening for food items over the sample period. Finally, the poor spend relatively more on food versus other non-food bar-coded products.

The Homescan data reveals that poorer households consume goods with lower unit-values, that are typically associated with lower quality products. A useful feature of the ACNielsen Food data is that in addition to the price and quantity of each UPC consumed, it provides detailed information on the weight or volume of each product. This allows us to compute unit values for each module – size pair. For instance, within the module "Milk", there are UPCs sold under many different sizes (e.g., 16 oz, 32 oz and 64 oz). A single-person

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[3] The U.S. Census Bureau selects a sample of approximately 7,100 households to build the CEX survey.
[4] While we have little information on response rates by different income groups, Nevo et al (2008) suggest that the coverage is good for all income groups, while response rates and measurement error is larger for higher income groups. We take some comfort in that we observe purchases for a large number of households in the upper decile of the income distribution.

household with income over $100,000 pays 32 percent more per oz of milk than a family of four earning $25,000 - $30,000. In particular, richer households consume a much higher fraction of organic milk. Figure 4A reports this result for all food products. For each module – unit of size pair (e.g., Milk – measured in ounces), we calculate the average unit value (price per ounce) paid by each group relative to the average unit value for this module – unit of size pair. More formally we compute :

$$(1) \qquad rel\_uv_{m,s,I,j} = \ln \frac{\overline{uv}_{m,s,I,j}}{\overline{\overline{uv}}_{m,s}}$$

where $\overline{uv}_{m,s,I,j}$ is the mean unit value for purchases in module '*m*' of products measured in size units '*s*' by households in income group '*I*' with '*j*' occupants, and $\overline{uv}_{m,s}$ is the average unit price paid by all households for products in module *m* with size units *s*. Figure 4A shows that the milk example is not atypical. Small households with large income routinely pay 30 percent more per unit than larger households with smaller incomes. Since the poor are only paying 5 percent less for the exact same UPC (Figure 4B), most of the lower average price for the poor therefore comes from selecting cheaper brands and, to a lesser extent, more economical sizes.

The raw price facts suggest that we can do better than categorizing households by income alone. Conditional on household income, a larger household is poorer. Henceforth we will categorize households by a per-capita measure: annualized sampled expenditures per capita. Since we know the exact purchase date of each item we can observe for how much of each year each household has been in the sample (overwhelmingly for the whole year), so we know the rate at which households are spending on products with UPCs. For each household, we use their entire sample history to sort them by expenditure-per-capita, a proxy for permanent income. Each household is given only one ranking for its entire duration in the sample. Due to the current lack of overlap in the samples, this is done separately for the Food sample and for the Non-Durable sample.

A second fact revealed by the Homescan data is that poorer households consume fewer food products than richer households, and this gap has been growing. We compute the number of unique UPC's purchased per household based on our food sample. We then calculate the average number of unique UPC's purchased per household by expenditure quintile (using only the "original" sample and not the larger household sample in 2004-2005). Figure 5A shows the number of UPCs per household by quintile. The lowest quintile has reduced the number of UPCs

they purchase relative to the richest households by an average of 20 percent. Moreover, while the expenditure per capita *and* the number of total UPCs in the sample has been growing over this period, both rich and poor households have reduced the number of varieties they consume. This suggests that the amount of overlap across households in the varieties that are consumed has been falling over this period.

Data limitations prevent us from computing the number of goods for non-food items by household over time. However, we can use the single quarter of household data to show the propensity of new goods to appear in the expenditures of each income group. The results presented in Figure 5B suggest that new non-food goods show up disproportionately in the expenditures of poorer households. Almost 70 percent of non-food expenditures by the poor in 2003 were on products that did not exist in 1994. For the top quintile, this proportion is under 50 percent. Many such new goods are simply inexpensive items sold in mass-merchandise stores. It is therefore likely that new goods from the non-food sample are relatively more beneficial for the poor than in the food sample.[5]

Finally, we document that the share of food consumption differs markedly across income groups. Using the household-level data in the Non-Durable database, we find that food modules account for 73 percent of expenditures for poorer households, but only 57 percent of expenditures for richer households (Figure 6). This highlights the differences that exist in the basket of goods consumed across income groups. These differences are also reflected in the products sold in different stores. For instance, in 2005 our Food database contains 61,119 food UPCs that were sold in either a Walmart or a Wholefoods (excluding random-weight products). Of these UPCs, 53,715 were sold in Walmart and 8,742 were sold in Wholefoods, with an overlap of just 1,338 UPCs sold in both stores. Just 15.3 percent of the UPCs in Wholefoods can be found in Walmart, while just 2.5 percent of Walmart UPCs can be found in Wholefoods.

III.   **Calculating Inflation Rates by Income Groups**

In this section we derive exact price indexes by income group. This differs from conventional or official CPI measures that are based on a representative household in the

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[5] In the fall 2009, we will update this calculation with a dataset that will allow us to compute the average number of UPCs per households over time for non-food items as well.

economy.[6] We build income-group specific price indexes by relaxing two standard assumptions underlying conventional price indexes. First, we allow the expenditure shares on each good consumed to differ between poor and rich. Second, we allow the introduction of new goods to affect the calculation of the cost-of-living index, and we permit the effect to differ across income groups. We adopt a nonparametric approach. We essentially allow for an underlying non-homothetic preference structure, but then approximate this structure with a series of non-symmetrical CES utility functions. Consumers may simply be on different points of the same Engel curve. Since we do not focus on understanding the reasons behind the differences in consumption behavior across income groups it is simplest to build consumer price indexes based on utility functions where the expenditure shares vary exogenously across income groups.[7]

We now write down these restrictions formally. The first step towards deriving an exact price index is defining a utility function over all goods in our sample. Suppose that the preferences of a particular household with income I can be represented by a two-level utility function:

(2) $$\Omega_{It} = F_{It}^{\alpha_I} NF_{It}^{1-\alpha_I}$$

where F_{It} is the sub-utility derived from the consumption of food products and NF_{It} is the sub-utility derived from non-food items in our sample. The Cobb-Douglas assumption between the aggregate food good and the aggregate of other goods is due to the current structure of our sample. We exploit the work of Sato (1976) and Vartia (1976) on ideal price indexes to simply assume that both F_{It} and NF_{It} are multi-level CES functions. Define U_{Ft} as the set of all possible food UPCs in period t. For future reference, each group I may consume a different set of UPCs, i.e. $U_{FIt} \subset U_{Ft}$, and the set of UPCs consumed in both periods t and t-1 by group I is given by $U_{FI} \subset U_F = U_{Ft} \cap U_{Ft-1}$ where U_F is the set of all common UPCs between periods. Non-food UPCs in U_{NF} are similarly arranged.

If the set of UPCs available for each group is fixed over time, Sato (1976) and Vartia (1976) have derived the exact price index in the case of any multi-level CES utility function. In

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[6] Statistical offices around the world compute changes in consumer prices for an "average" person in the economy. In the US, the BLS conducts "Point of Purchase Surveys" to assess where people are buying their products. These surveys use demographic and socioeconomic information that allows BLS to monitor how well the selected interviewers represent the overall population.

[7] Of course an alternative way to proceed is to have the same utility function across income groups, but allowing for non-homothetic preferences, but this may result in significant loss of flexibility in capturing consumer preferences.

the case where expenditure shares of particular UPCs are allowed to vary by income group *I*, the "common goods" exact price index is defined as follows,

$$(3) \qquad \pi_{FI} = \prod_{u \in U_{FI}} \left(\frac{p_{uFIt}}{p_{uFIt-1}} \right)^{w_{uFIt}}$$

This is the geometric mean of the price changes of individual UPCs *u* that belong to the set U_{FI}, where the weights are ideal log-change weights.[8] These weights are computed using expenditure shares of each income group, s_{uFI}, in the two periods, as follows:

$$(4) \qquad s_{uFIt} = \frac{p_{uFIt}c_{uFIt}}{\sum_{u \in U_{FI}} p_{uFIt}c_{uFIt}}$$

$$(5) \qquad w_{uFIt} = \frac{\dfrac{s_{uFIt} - s_{uFIt-1}}{\ln s_{uFIt} - \ln s_{uFIt-1}}}{\sum_{u \in U_{FI}} \left(\dfrac{s_{uFIt} - s_{uFIt-1}}{\ln s_{uFIt} - \ln s_{uFIt-1}} \right)}$$

where *c* denotes consumption quantity. The numerator of (5) is the difference in shares over time divided by the difference in logarithmic shares over time. The weights *w* capture all we need to know about how consumers in group *I* value each UPC and how prepared they are to substitute it for other products. Consider what happens in response to a price rise for UPC *u*. If consumers are very prepared to substitute other products for *u*, then the expenditure share on *u* will decline substantially and the weight function in (5) gives a weight much closer to the lower expenditure share, assuming that the denominator in (5) is close to 1. Products that are highly substitutable for other products can receive a much lower weight than their average expenditure share. For products where the expenditure shares barely move in response to a price change, the weight is very close to the simple average expenditure share. We will show that this index in practice gives nearly identical results to the much better known Fisher ideal index. The flexibility of its structure allows us to account for the different first-order impacts of price changes on the welfare of different income groups owing to different expenditure shares, together with different second-

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[8] As explained in Sato (1976), a price index *P* that is dual to a quantum index, *Q*, in the sense that *PQ = E* and shares an identical weighting formula with *Q* is defined as "ideal". Fischer (1922) was the first to use the term ideal to characterize a price index. He noted that the geometric mean of the Paasche and Laspayres indices is ideal.

order impacts coming from different willingness to substitute across varieties. These second-order effects turn out to be very important.

The introduction of new goods implies that a true cost-of-living index will differ from the common-goods exact price index defined in (3). Feenstra (1994) showed how to modify this common-goods exact price index for the case of different, but overlapping, sets of varieties in the two periods. Suppose that there is a set of UPCs $U_{FI} \neq \varnothing$ that are available in both periods, and for which the taste parameters are constant. Extending the work of Feenstra (2004) we can derive different cost-of-living indexes by income group from the utility structure allowing for product creation and destruction:

(6)
$$COLI_{FI} = \pi_{FI} \times \left(\frac{s_{FIt}^c}{s_{FIt-1}^c} \right)^{\frac{1}{\sigma_F - 1}},$$

$$\text{where } s_{FI,t}^c = \frac{\sum_{u \in U_{FI}} p_{uFIt} c_{uFIt}}{\sum_{u \in U_{FIt}} p_{uFIt} c_{uFIt}}.$$

$COLI_{FI}$ is the cost-of-living index (or exact price index) for food for group I adjusted for new-goods bias between periods t and $t-1$, and $s_{FI,t}^c$ is the share of common UPCs in food consumed by group I to the total food consumption of group I. We define $COLI_{NFI}$ for non-food items similarly.

Given the Cobb-Douglas aggregator between food and non-food items the "common" goods aggregate exact price index for all items in our sample is:

(7)
$$\pi_I = \pi_{FI}^{\alpha_I} \pi_{NFI}^{1-\alpha_I}$$

where the weights α_I are the simple expenditure shares in Figure 5C. Explicitly allowing for product turnover, we obtain the following expression for the relationship between the conventional inflation measures and changes in the cost-of-living index:

(8)
$$COLI_I = \pi_{FI}^{\alpha_I} \times \pi_{NFI}^{1-\alpha_I} \times \left(\frac{s_{FIt}^c}{s_{FIt-1}^c} \right)^{\frac{\alpha_I}{\sigma_F - 1}} \times \left(\frac{s_{NFIt}^c}{s_{NFIt-1}^c} \right)^{\frac{1-\alpha_I}{\sigma_{NF} - 1}}.$$

Overall inflation adjusted for new-goods bias is comprised of two different components: 1) $\pi_{FI}^{\alpha_I} \times \pi_{NFI}^{1-\alpha_I}$ is the "common-goods" exact price index for group *I* for non-durable goods; and 2)

$$\left(\frac{s_{FIt}^c}{s_{FIt-1}^c} \right)^{\frac{\alpha_I}{\sigma_F-1}} \times \left(\frac{s_{NFIt}^c}{s_{NFIt-1}^c} \right)^{\frac{1-\alpha_I}{\sigma_{NF}-1}}$$ captures the role that product turnover, or new goods bias, plays for

each group.

The geometric average of $s_{FI,t}^c / s_{FI,t-1}^c$ ratios captures the difference (or bias) between a true cost-of-living index relative to the common-good price indexes like the CPI. Mechanically, when the share of new UPCs consumed by group *I* in period *t* is larger than the share of UPCs that have disappeared from group *I*'s basket in period $t-1$, this $s_{FI,t}^c$ ratio is smaller than 1. The smaller is this share ratio, the smaller is the overall inflation rate that takes product turnover into account relative to a conventional (common-goods) price index that does not.

The inflation rate in (8) also depends on the elasticities of substitution σ_F and σ_{NF}. For instance, as σ_F grows, the term $\frac{1}{\sigma_F-1}$ approaches zero, and the bias term $\left(\frac{s_{FIt}^c}{s_{FIt-1}^c} \right)^{\frac{\alpha_I}{\sigma_F-1}}$ becomes unity. When existing varieties are close substitutes to new or disappearing varieties, changes in varieties will not have a large effect on the difference between π_I and $COLI_I$. By contrast, when σ_F is small, varieties are not close substitutes, $\frac{1}{\sigma_F-1}$ is high, and therefore new varieties are very valuable and disappearing varieties are very costly. In this case, the conventional price index is a biased measure of the true cost of living index.

We can now formally see in (8) the two main assumptions that we relaxed relative to standard official measures of inflation. The first difference with a standard representative agent setup is that the inflation of common goods over time, π_I, has weights that depend on the group *I*. Second, the last two terms in (8) allow for new and disappearing products to impact income groups differently.

IV.   Inflation Rates by Income Groups, 1994 – 2005

(i) Food 1994-2005

We use the Food database to compute the common-goods food inflation rate, π_{FI} (the first term in equation (8)), by income percentile for 1994 to 2005. For 1998 – 2005 we use precisely the methodology detailed in Section III. Prior to 1998 the lack of household detail prevents us from implementing the Sato (1976) and Vartia (1976) ideal weights for the common-goods price index, so instead we use simple expenditure shares by quintile in 1998 to construct a Paasche index for prices changes between 1994 and 1998. The first three columns of Table 2A report π_{FI}, the food inflation rate for common goods by income group. For 1994-2005, π_{FI} ranged from 8.7 percent for the 10th percentile to 17.2 percent for the 90th percentile and 18.3 percent for the top 5 percent of households. Overall, the prices of common food items have been rising considerably faster for the rich than for the poor.

We report the results for common food goods more flexibly in Figure 7. The inflation rate for percentile P is calculated by grouping households between percentiles P-5 to P+5. At the upper part of the distribution we have to modify this slightly, so that by the 99th percentile we are simply looking at the top 2 percent of households. The food inflation rate for common-goods between 1994-2005 increases steadily through the income distribution, from just 8 percent at the bottom of the distribution to 22 percent near the top (99th percentile). In particular, the inflation differential in common-goods for food items between the 90th and 10th percentile of the income distribution was 8.5 percentage points during the 1994 – 2005 period.

We also calculate the new goods bias (the third term in equation (8)) for 1998-2005 from the Food database using the median substitution elasticity of 11.5 estimated by Broda and Weinstein (2009) for σ_F and σ_{NF}. The results are reported in column 5 of Table 2A, and range from -2.9 percent for the 10th percentile to -3.9 percent for the 90th percentile. New goods are therefore contributing substantially to the well-being of all groups, by 0.5 percent annually on average. The results are almost unchanged with a definition of new goods based on the geographic area where households purchases are made.[9] The lack of household detail prior to 1998 prevents us from calculating the new goods bias by group for 1994-1998. However, we

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[9] We also calculated the bias based on a measure of new goods that more carefully captures the notion of geographical market segmentation (where new goods are restricted to the metropolitan area where households live, or the interaction of store-id and metropolitan area). In this case we restricted the sample to a fixed number of households throughout the period to prevent any sampling concerns. The bias based on a definition of new goods that is restricted to a particular geographical area is almost identical to that based on the market as a whole.

find that the new goods bias for all consumers for 1994-1999 calculated using food modules in the aggregate Non-Durable database follows roughly the same annual rate as 1998-2005, at -0.6 percent per annum. For the purpose of our combined inflation rate calculations we extrapolate the 1998-2005 bias for each percentile back to 1994. Our new goods bias estimates for food appear in columns 4 to 6 of Table 2A.

Combining the common-goods inflation and new-good bias estimates for food items yields the overall change in the food cost-of-living index between 1994-2005, which ranges from 3.7 percent for the 10th percentile to 10.2 percent for the 90th percentile, and 11.1 percent for the top 5 percent of households. The solid line in Figure 7A reports the changes of the cost-of-living index for food items. Overall, the difference in the changes of the food cost-of-living indexes between the 90th and 10th percentile of the income distribution was 6.5 percentage points during the 1994 – 2005 period.

(ii) Non-food 1994-2003

We use the Non-Durable database to compute the non-food inflation rate, π_{NFI} (the second term in equation (8)), by group *I* for 1994-2003. Since we only have one quarter of household-level data for nonfood items (3500 households in 2003Q4) we employ simple expenditure weights by percentile in 2003 to calculate a Paasche price index for non-food common goods for 1994-2003. Table 2B shows that non-food common goods inflation varies from 11.7 percent for the 10th percentile to 18.7 percent for the 90th percentile and 20.5 percent for the top 5 percent of households in our sample. For ease in comparisons with the food sample, we simply extrapolate these results for 2004 and 2005 in column 2 of Table 2B. We show below how results are qualitatively unchanged if we used the shorter comparison period.

The lack of a second year of household data for non-food items prevents us from completing calculations of the new goods bias by income group (the fourth term in equation (8)), but we can still calculate the aggregate bias. For 1994 to 2003 the "aggregate" data for nonfood items shows the average new goods bias to be -6.3 percent, or -0.7 percent annually. Given the limitations of our dataset, we simply set the bias for each group equal to the average bias and extend the results to the years 2004 and 2005 for comparison purposes only.[10] In Table 2C we

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[10] Access to the complete household database from 1994 onwards will enable us to compute CES cost-of-living for non-food items as we currently do for food products.

also present results just for 1994-2003 where we have simply dropped the last two years of food data to align that sample with the shorter non-food sample, and the same picture emerges.

We again present the results more flexibly in Figure 7B. The estimated non-food inflation rate is more volatile for two reasons. The main reason is the smaller amount of expenditures in the household-level nonfood sample – our weights are derived from just 3 months of expenditures for 3500 households. The second reason for volatility is that non-food purchases can be more lumpy, which contributes to sample variance. Yet the pattern in the data seems clear: the inflation rate is higher for higher-income households. It averages about 5 percent at the bottom of the sample, 10 percent in the middle and 15 percent for households that spend the most.

(iii) Combined Cost of Living Index ($COLI_I$)

We use our disaggregated household expenditure data for 3500 households in 2003 to construct weights on both food and non-food items by income group (α_I, $1 - \alpha_I$) which are necessary to calculate the cost of living index for all items using equations (7) and (8). We use this sample to construct weights on the share of food versus non-food items across expenditure groups (Figure 5C and the last column of Table 2C). Not surprisingly, poorer households spend proportionally more on food (70.8 percent) than do richer households (49.6 percent).

The COLI results for 1994-2005 are reported in Table 2C and Figure 7C. For the 10th percentile, the cost-of-living inflation was just 4.3 percent, while for the 90th percentile it was 11.9 percent, and 13.5 percent for the 95th percentile of households in our sample. If we focus on the 1994-2003 data to eliminate the small but crude extrapolations for non-food items, the story is much the same. Inflation for 1994-2003 was 3.4 percent for the 10th percentile, 10.0 percent for the 90th percentile and 11.4 percent for the 95th percentile (Table 2C, 6th column). Inflation for rich households is rising roughly 0.7 per cent per annum faster than for poor households.

The implications of this for long-term income growth and inequality measures are potentially profound. Table 3 compares the differences in COLI for different income groups to the changes in common measures of income inequality over the same period. The extent of the offsetting effect that the COLI differentials have on standard inequality measures depends on how extensively the basic fact uncovered in our sample applies to expenditures outside of those on non-durable goods. Assuming that our findings are only applicable to non-durable goods

(30.4 percent of household expenditure), then around half of the increase in conventionally measured inequality during 1994 – 2005 is the result of using the same price index for non-durable goods across different income groups. The share varies from 87 percent for the $80^{th}/20^{th}$ income ratio to 36 percent for the $90^{th}/10^{th}$ ratio. That is, using income specific non-durable inflation rates the $80^{th}/20^{th}$ ratio rises 0.3 percent over this period (instead of the official 2.1 percent), while the $90/10^{th}$ measure rose 3.5 percent (rather than the official 5.7 percent).

Table 3 also shows the implications on inequality measures if durable goods and service sectors also exhibited similar increases in price dispersion as that observed for non-durable goods over this period. In this case using income specific inflation rates the $80^{th}/20^{th}$ ratio falls during the 1994 – 2005 period by 4.0 percent (instead of rising by 2.1 percent as in the official measurement), while the $90/10^{th}$ measure falls by 1.6 percent (rather than the official rise of 5.7 percent). In the next section we present evidence that suggest that our results may not only extend beyond our sample of goods but also beyond the time period being studied.

Income-specific inflation measures suggest that the fruits of economic progress may have been much more evenly distributed than we currently believe. The reason for these results is deep yet simple – changes in the price distribution are causing the mapping from (log) nominal income to welfare to become flatter (as in Figure 2). Imagine that in 1994 the mapping between permanent income and welfare is given by $ln\ W = ln\ Y$. Using census data on household income as our proxy for the distribution of income, the relationship between income and welfare in 1994 is depicted by the dashed line in Figure 8. The solid line depicts the same relationship in 2005. The dispersion of household income has increased, but the same is not true for welfare as relative price have changed in favor of goods purchased by poor households (in terms of the graph, the 2005 line is flatter than the 1994 line). We believe that this has implications for how we should interpret most existing studies of inequality, which focus on the horizontal axis (income distribution) rather than on the vertical axis (welfare distribution).

V. What Drives Our Results and Why They Extend Beyond Our Sample

We show that rising price dispersion within narrowly defined products has been an unmistakable pattern of the data, and that it is likely behind the rapid rise in prices for rich relative to poor consumers for two reasons. Firstly, poor households consume a disproportionate amount of "primary" qualities of the good (for example, a glass that may cost $1 at the local

mass-merchandise store) and relatively less on the "secondary" qualities of the good (characteristics we intuitively think of as "quality", such as a hand-made Riedel Sommelier 24% lead crystal Bordeaux glass that may cost $80) which have increased most in price. Second, poorer households may be more willing to substitute away from products with rapidly rising prices. Thus, the "substitution bias" may be higher for poorer households. In this section, we document the fact that price dispersion has been rising in our sample, its consequences for price measurement, and examine how these patterns are not specific to our sample or time period.

Rising price dispersion is apparent in both our food sample and our non-food sample. To describe this pattern, we calculate the unit value for each UPC, e.g., the price of an ounce of milk. For each module - quantity-unit pair (such as Milk, measured in ounces), we rank purchases by unit value. We then calculate percentiles of the distribution of unit prices for each module - quantity-unit pair. The p-th percentile is the price where p-percent of the goods by value (not by quantity) sell at or beneath that price. The use of value rather than quantity to define the percentiles is to reduce problems associated with measurement error in quantities in an international trade database we use below. Figure 9A shows the unit price of food items at the 50th percentile has been rising relative to the 10th percentile, and that prices at the 90th percentile have been rising relative to the 50th. Figure 9B shows rising price dispersion for non-food products in our sample.

How can this increased price dispersion affect inflation differentials by income group? The fact that in most categories the poor systematically choose lower unit-value items (as we described in section II), suggests that they place a relatively low importance on secondary qualities of a product, so that poorer households keep substituting towards inexpensive varieties. These differences may also be driving the differences in shopping trends between rich and poor. The rising price dispersion is particularly apparent between stores that cater to consumers of different income levels. For a similarly-defined food product (an ounce of milk, for example), the unit prices at Walmart were 53 percent less than at Wholefoods in 2005. And, not surprisingly, the share of expenditures of the poor relative to the rich has risen sharply for purchases in Walmart relative to Wholefoods. Figures 10A and B show the evolution of the share of expenditures from shopping at Walmart and Wholefoods by different income groups. The patterns suggest a sharp rise in the expenditures in Walmart by the poor and in Wholefoods by the rich over the period studied.

Moreover, poorer consumers also appear more willing to substitute across varieties than richer consumers. When the price of one item goes up, the poor are more likely to shift expenditures to another variety. A simple exercise using our household data for Food from 1998 to 2005 illustrates this point. We first match households across years to eliminate variation from household-specific tastes, so that inflation between *t-1* and *t* is calculated using the same households. We then calculate the log-change in two traditional price indexes by income percentile: a Laspeyres price index and a Paasche price index. A Laspeyres price index weights prices using quantities in the earlier period – it therefore ignores second-order effects from product-substitution and therefore overstates true inflation. The price of the basket that the poor used to purchase is rising as rapidly as for wealthier households and more rapidly than for households in the middle of the income distribution. The Paasche price index uses quantities from the last period to weight price changes and therefore picks up this substitution effect. But the Paasche index understates true inflation because it does not capture some of the welfare cost of making this substitution.

Figure 11A shows that the poor are doing much more substitution than the rich – the very rich appear to respond little to price changes for food items. Moreover, our Sato-Vartia price index captures both these effects and lies neatly in the middle of the Laspeyres and Paasche indexes. Since Figure 11A is in log-points, the better known Fisher Index is the average of the Laspeyres and Paasche indexes, and in Figure 11B we see it is almost indistinguishable in practice from the Sato-Vartia index.

Our results are also mostly driven at a very fine level of product detail. We show this by eliminating detail from our data and constructing price indexes for Food for 1994-2005 at the module level (640 categories) using average expenditure weights. We then use income-specific expenditure weights at the module level to weight price changes. Figure 12 shows that almost all of our food result disappears when we do this. This implies that our results are not driven by the price of coffee relative to the price of water, but by the price of Illy versus the price of Folgers and Taster's Choice. Whenever prices become more dispersed at this fine level, a price index for poorer consumers is likely to rise less rapidly than one for wealthier households. Poorer consumers shift purchases to products that have been rising in price less rapidly. Since poorer consumers already systematically purchase less expensive goods (Figure 4A), this suggests that

there is more room for this substitution process if the dispersion of prices of similarly defined goods (such as an ounce of milk) has been increasing over time.

The uniqueness of the Homescan data is that we can make explicit adjustments for quality using simple techniques. But other publicly available data exhibit the same price dispersion pattern that is driving our results for a broader range of goods and services. The problem with these data is that quality adjustment is more difficult, but the price patterns are still suggestive. The three nondurable goods categories that are mostly not in our sample are food away from home (6.7 percent of household expenditures), gasoline and motor oil (5.0 percent) and apparel (4.8 percent). While we do not expect our finding to apply strongly to gasoline, we have evidence that it is strong in food away from home and apparel. The evidence for food away from home comes from two Zagat restaurant surveys for Chicago, one in 1988 and one in 2009. These surveys include a measure of price and quality (evaluated by diners). Figure 13 plots a simple nonparametric estimate of Chicago restaurant prices by quality (the sum of the ratings for food, décor and service). The figure suggests that inflation for restaurants with low quality ratings has been about 40 log points between 1988 and 2009 or almost 2 percent annually, while restaurants with higher ratings have experienced inflation around 60 log points or almost 3 percent annually. As in our non-durable sample, this rising relative price of quality is the proximate cause of our real inequality result.

The same patterns are even more pronounced in clothing. Monthly US Imports of Merchandise data contains detailed shipment information on over 3,000 textile, clothing and footwear products. We use this data to construct percentiles of the unit import price distribution for each of these products, where the p-th percentile is the price where p-percent of the product by value sells at or beneath that price. Figure 14 summarizes these results. In 1994 the typical 50-th percentile item sold for 56 log-points more than the equivalent 10-th percentile item, while the 90-th percentile item sold for a 74 log-point premium over the 50-th percentile. By 2005 the 50-10 premium had risen to 70 log-points and the 90-50 premium rose to 96 log-points. Over this 11-year period, the price of an item at the 90-th percentile rose 3 percent annually relative to its 10-th percentile equivalent.

Additional evidence can be provided by international trade. Trade data values and quantities have long been collected by detailed product classification. US trade data is available electronically since 1972. From 1990-2007, monthly Census Bureau DVDs "*US Imports of*

Merchandise" were used to construct percentiles of the price distribution for each HTSUSA 10-digit product (typically over 3 million observations each year on around 15,000 products). These are summarized in Figure 15A for all products, which shows a steady increase in price dispersion. Similarly more aggregate annual US Import data from 1972-1988 contain about 125,000 observations annually on around 10,000 TSUSA 7-digit products.[11] Figure 15B shows that rising price dispersion has been a feature of this data since 1972, suggesting that a price index for the poor for all goods has likely been declining relative to the price index of the rich decades before the start of our sample period.

The evidence outside of tradable goods is harder to obtain. However, a recent paper by Enrico Moretti (2008) shows that the price of housing has been rising much faster for higher income earners than for lower-income earners, enough to erode about half of the rising return to college between 1980 and 2000. While the mechanisms underlying that paper may differ, it seems that price dispersion that has been present in non-durable goods has also been a pattern of most market-provided goods and services for decades. This makes it likely that our formal price index results using the ACNielsen Homescan data are not peculiar to that sample or time period, but may indeed be representative of consumer expenditures generally.

VI. Conclusion

This paper uncovers a new fact: non-durable inflation for poorer households has been substantially lower than for richer households. The result is surprising for a number of reasons. First, empirical studies have been computing price indexes for different types of household characteristics without finding large differences. However, all of our results come from an increase in price dispersion at a fine level of product detail, and hence was not captured in previous studies. Second, a large literature has focused on the rising inequality observed in official statistics, but have mostly abstracted from the fact that these official measures are based on a single price index for a representative consumer. This assumption is not crucial in a world with a stationary relative price distribution or where an identical basket of goods is consumed by different income groups. However, using household data on non-durable consumption, we

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[11] US trade data moves to a new classification in 1989, but the most detailed Census Bureau data DVDs were first released in 1990.

document that the relative prices of low-quality products that are consumed disproportionately by low-income consumers have been falling over this period.

This fact implies that measured against the prices of products that poorer consumers actually buy, their "real" incomes have been rising steadily. As a consequence, we find that around half of the increase in conventional inequality measures during 1994 – 2005 is the result of using the same price index for non-durable goods across different income groups. Moreover, given that the increase in price dispersion does not seem to be specific to our sample or time-period, the overstatement in the increases in inequality from official measures can be even more significant, changing our view of how progress has been distributed in recent decades substantially.

While we have described that rising price dispersion can account for the inflation differential across income-groups, in future research we plan on focusing on the deeper economic reasons driving this fact. We have three alternatives that could be potential explanations. First, much of our result appears to be driven by the availability of low cost alternatives valued by lower-income households. International trade with developing countries is an increasingly important source of inexpensive products sold to consumers – over 50 percent of non-energy imports in recent years come from developing countries compared with under 35 percent in 1990.[12] We have found a strong negative correlation between the changes in prices by product module and the change in Chinese trade in that same module over this time period. This strongly suggests that trade with China may have partly driven the increase in inflation differentials by income-group.[13] The same negative correlation is not present with trade from developed countries.

Second, if wealthier consumers spend more in skill-intensive products and services, then on balance they are purchasing relatively more of the labor of skilled workers. An increase in the skill premium will be reflected in the prices of the products and services that embody their labor. However, price indexes that do not allow for the basket of goods to differ across households will not capture this effect. Finally, the dramatic change in shopping patterns in recent decades could

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[12] The NICS have been classified as developing for this entire period for consistency. The fact of sharply rising exports from developing countries does not depend on this.

[13] We reported these results in a previous version of the paper. We have removed this analysis from this paper as we undertake a more ambitious exercise to more precisely capture the role that trade with China has played in explaining the fact uncovered in this paper. The UPC-level Homescan data lacks an important detail – the country of production of the good. Two teams of undergraduates are scanning UPC codes and entering country of origin details – which can be determined for most products, especially nonfood items.

possibly be thought as an exogenous change in productivity in favor of the poor. The advent of supercenters could imply that final productivity in low-priced goods has increased by more than for other goods. This could help explain the change in shopping patterns across households together with the price effects we find in this paper. We hope to explore these possibilities in future research.

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Table 1A: ACNielsen "Non-Durable" Homescan Database 1994, 1999-2003

		1994	1999	2000	2001	2002	2003
# Households	Aggregate	41500	55000	55000	55000	55000	55000
# UPCs	Aggregate	532789	651343	666445	658055	690036	697272
# Modules	Aggregate	1097	1096	1095	1093	1092	1093
# Households	Household						3500
# UPCs	Household						366324
# Modules	Household						1060

Table 1B: ACNielsen "Food" Homescan Database 1994, 1999-2003

		1994	1998	1999	2000	2001	2002	2003	2004*	2005
# Households	Sample 1		7624	7124	7523	8216	8684	8833	8533	8225
# UPCs	Sample 1		237766	237302	244556	248875	257935	259802	256825	255805
# Modules	Sample 1		616	636	636	635	640	639	640	640
# Households	Samples 1+2								39572	38857
# UPCs	Samples 1+2								379202	381938
# Modules	Samples 1+2								640	640

*2004 data file for Frozen; Meat; and Produce items was corrupted. 2005 data substituted here for summary statistics.

Table 2A: Food Inflation 1994-2005

Percentile	Common 94-98	Common 98-05	Common 94-05	Bias 94-98*	Bias 98-05	Bias 94-05	Food 94-05
10	0.045	0.040	0.087	-0.017	-0.029	-0.046	0.037
20	0.048	0.042	0.092	-0.017	-0.030	-0.047	0.041
50	0.066	0.046	0.115	-0.019	-0.033	-0.051	0.058
80	0.084	0.061	0.150	-0.020	-0.035	-0.055	0.087
90	0.098	0.067	0.172	-0.022	-0.038	-0.060	0.102
95	0.101	0.074	0.183	-0.023	-0.039	-0.061	0.111

* Extrapolated at 1998-2005 rate.

Table 2B: Nonfood Inflation 1994-2005

Percentile	Common 94-03	Common 03-05*	Common 94-05	Bias 94-03	Bias 03-05*	Bias 94-05	Nonfood 94-05
10	0.117	0.025	0.145	-0.063	-0.014	-0.077	0.057
20	0.078	0.017	0.096	-0.063	-0.014	-0.077	0.012
50	0.131	0.028	0.162	-0.063	-0.014	-0.077	0.073
80	0.155	0.033	0.193	-0.063	-0.014	-0.077	0.101
90	0.187	0.039	0.233	-0.063	-0.014	-0.077	0.138
95	0.205	0.042	0.256	-0.063	-0.014	-0.077	0.160

* Extrapolated at 1994-2003 rate.

Table 2C: Combined Inflation 1994-2005

Percentile	Common 94-05	Bias 94-05	COLI 94-05	Food 94-03	Nonfood 94-03	Combined 94-03	Food Weight
10	0.103	-0.055	0.043	0.029	0.046	0.034	0.708
20	0.094	-0.057	0.031	0.038	0.010	0.028	0.671
50	0.133	-0.061	0.064	0.051	0.059	0.054	0.619
80	0.169	-0.065	0.094	0.080	0.082	0.081	0.555
90	0.201	-0.068	0.119	0.089	0.111	0.100	0.518
95	0.219	-0.069	0.135	0.100	0.129	0.114	0.496

Table 3: The impact of income specific COLIs in standard measures of inequality

	Official Household Inequality Ratios (Census Bureau)			
	80/20th	90/10th	95/10th	95/20th
2005	4.780	11.170	14.710	8.660
1994	4.680	10.570	13.680	8.180
Change 2005 - 1994	0.021	0.057	0.075	0.059
	Inflation Differentials (Table 2)			
	80/20th	90/10th	95/10th	95/20th
1994 - 2005	0.061	0.073	0.088	0.101
Average per annum	0.005	0.006	0.008	0.009
	"Real" Inequality measurs based on Non-durable Inflation rates specific to income groups			
	80/20th	90/10th	95/10th	95/20th
Change 2005 - 1994	0.003	0.035	0.048	0.028
	"Real" Inequality measurs based on Aggregate Inflation rates specific to income groups			
	80/20th	90/10th	95/10th	95/20th
Change 2005 - 1994	-0.040	-0.016	-0.013	-0.042

Figure 1: Real Household Income Levels by Percentile
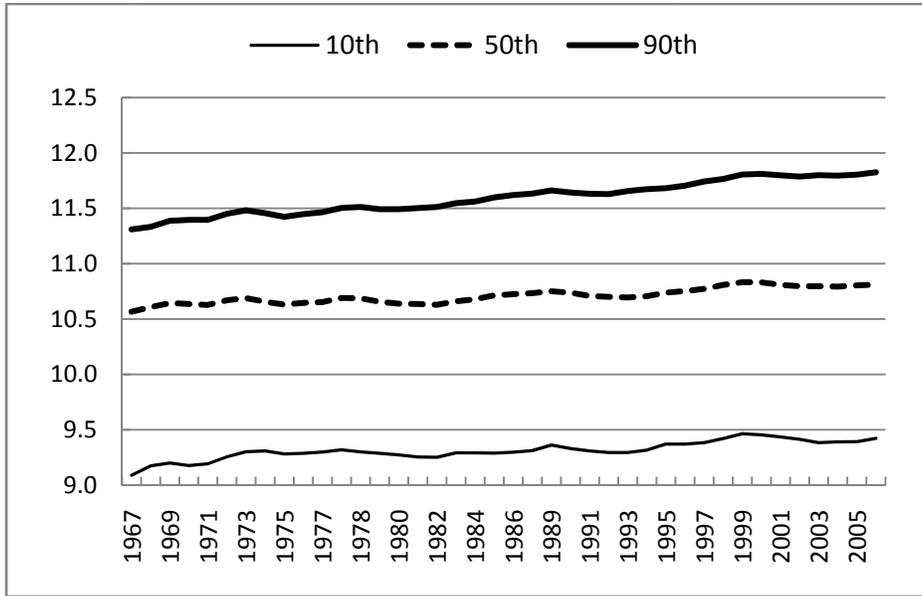
Source: Census; Selected Measures of Household Income Dispersion: 1967-2007

Figure 2: Hypothetical Mappings From Income To Welfare
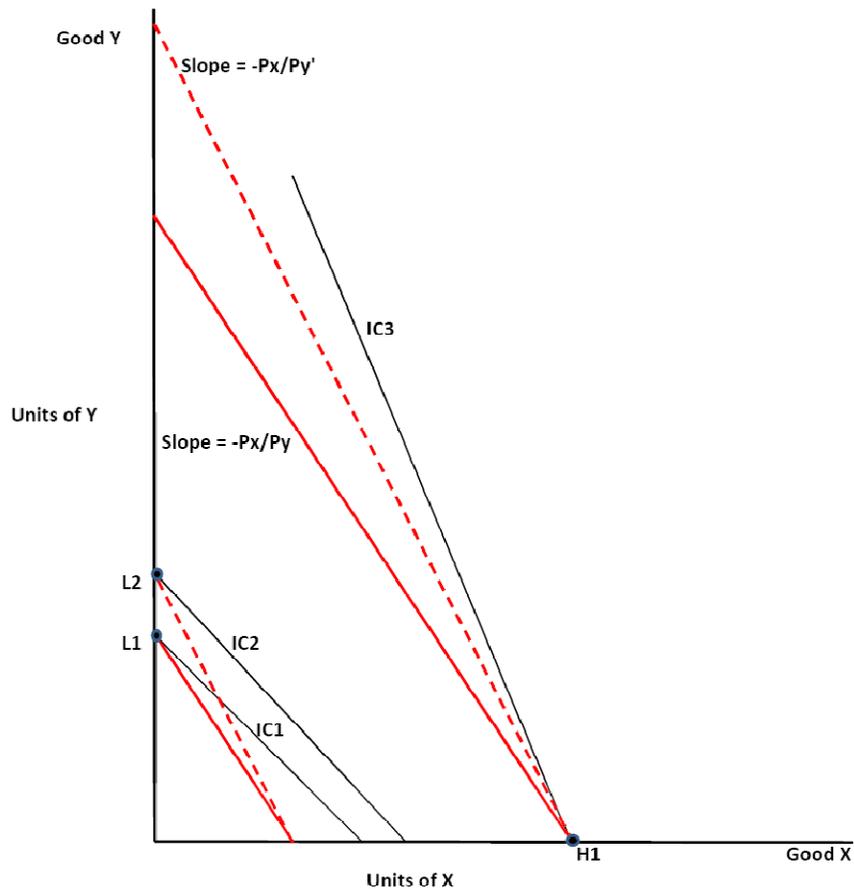
Figure 3A: Household Income Distribution in ACNielsen Sample

Number of Households by Income Group (2005)*

* Total Number of Housholds included : 38746
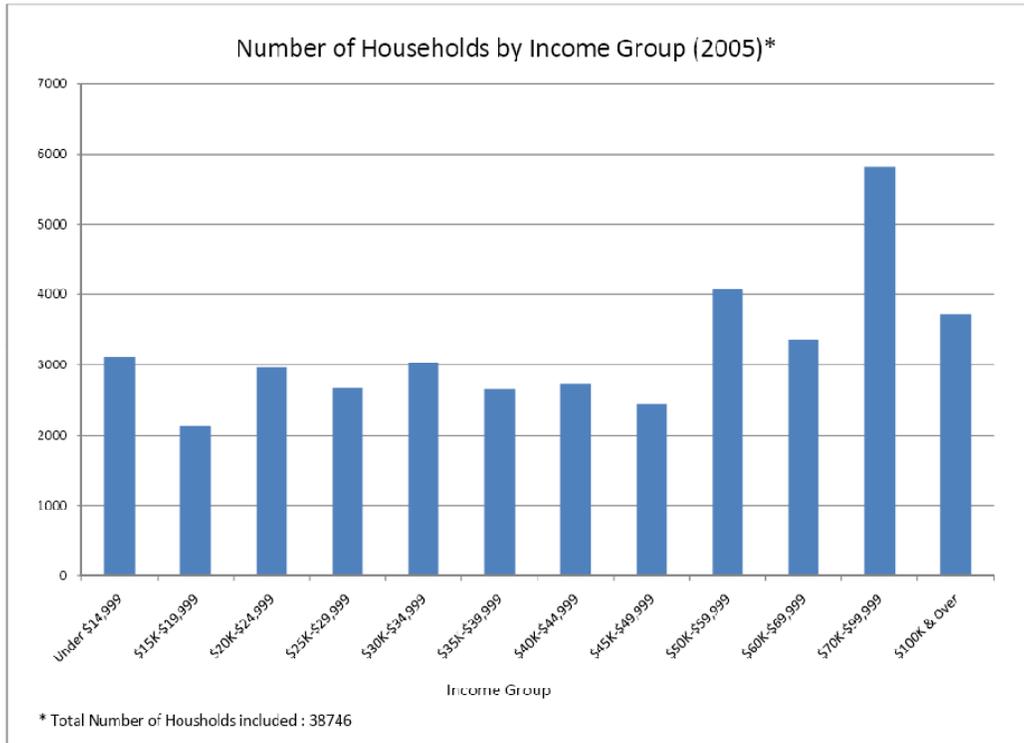
Figure 3B: Household Head Education Distribution in ACNielsen Sample

Number of Households by Education Level (2005)

27
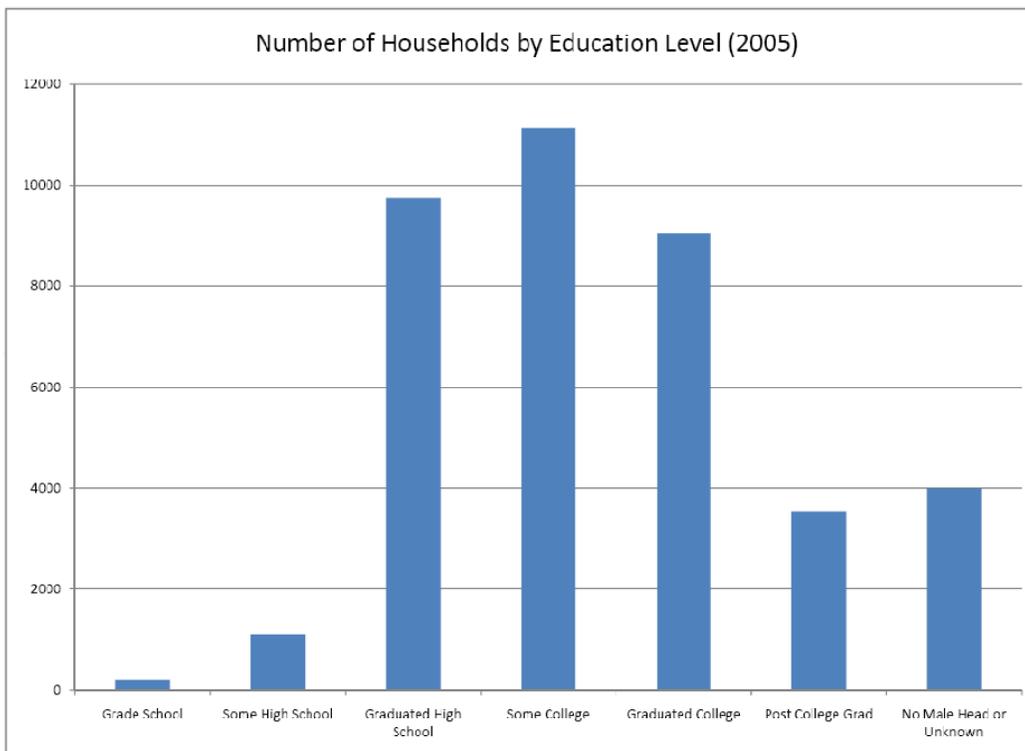
Figure 4A: Relative Prices Paid for Similarly Defined Goods

Unit-Price Paid by Product Category
by Household Size and Income

Legend: 1   2   3   4+

y-axis: 0.20, 0.15, 0.10, 0.05, 0.00, -0.05, -0.10, -0.15

x-axis: Under $10K, $10K - $14,999, $15K-$19,999, $20K-$24,999, $25K-$29,999, $30K-$34,999, $35K-$39,999, $40K-$44,999, $45K-$49,999, $50K-$59,999, $60K-$69,999, $70K-$99,999, $100K & Over
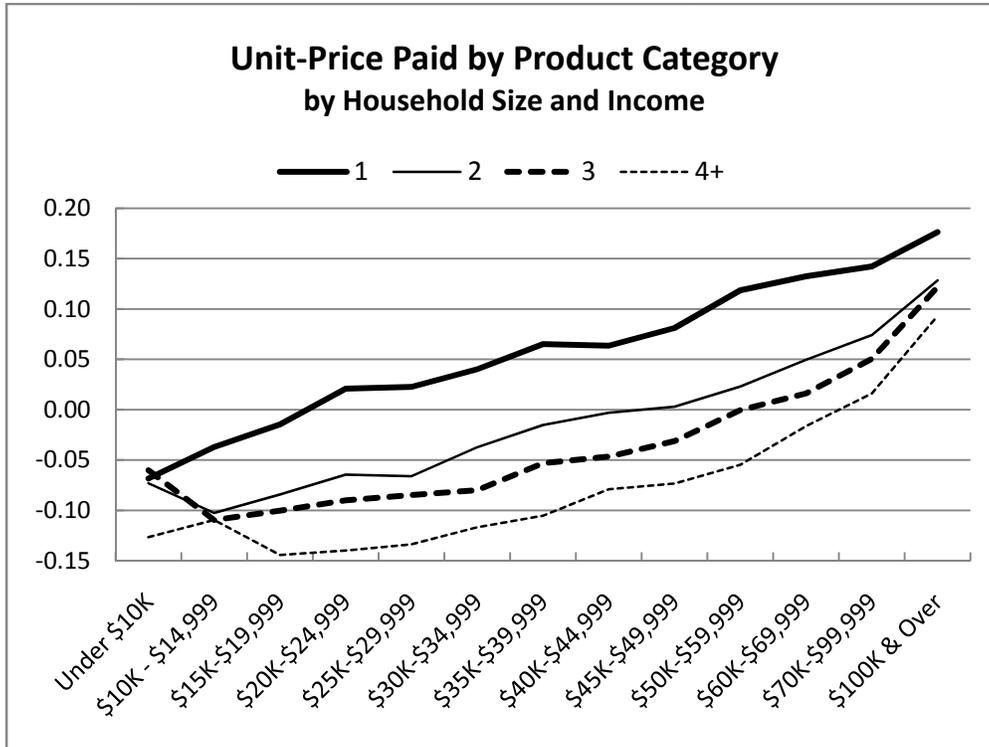
Figure 4B: Relative Prices Paid for Identical UPC

Price Paid by UPC
by Household Size and Income

Legend: 1   2   3   4+

y-axis: 0.10, 0.05, 0.00, -0.05

x-axis: Under $10K, $10K - $14,999, $15K-$19,999, $20K-$24,999, $25K-$29,999, $30K-$34,999, $35K-$39,999, $40K-$44,999, $45K-$49,999, $50K-$59,999, $60K-$69,999, $70K-$99,999, $100K & Over
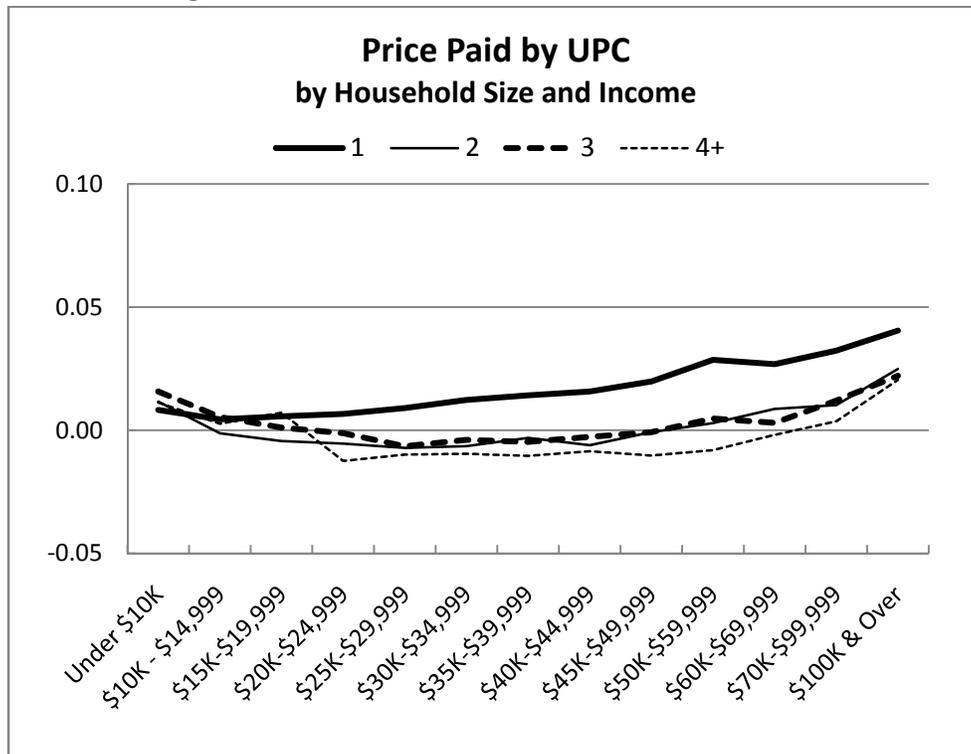
Figure 5A: UPCs per Household in ACNielsen Sample

Number of UPC's Per Household (Log)

Quintile 1 ——— Quintile 3 ----- Quintile 5 ——— Top5% -------
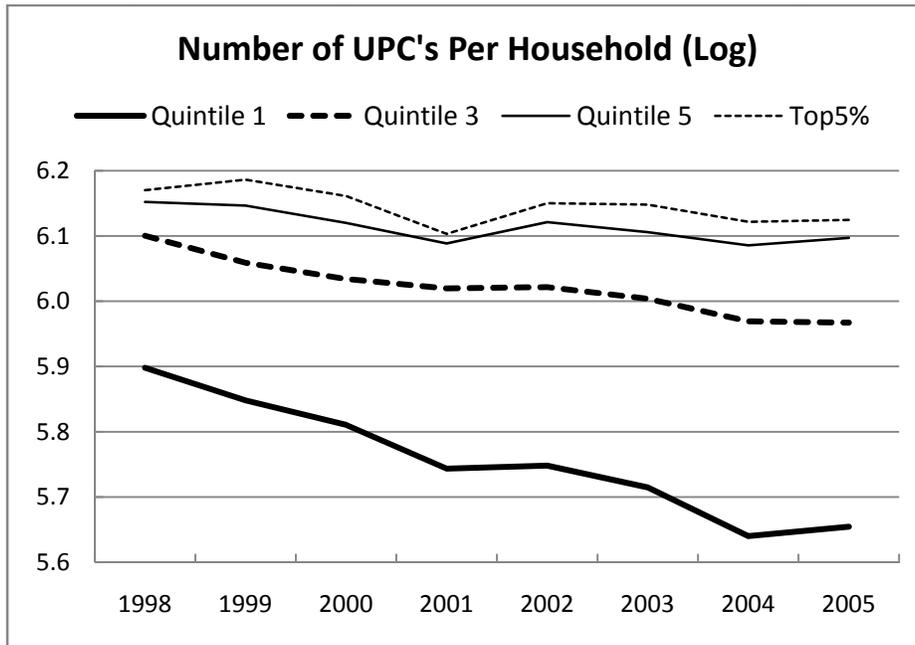
Figure 5B: Non-Food Expenditure Shares on New Goods by Quintile 2003

Nonexistent in 1994

Nonexistent in 1999

Quintile
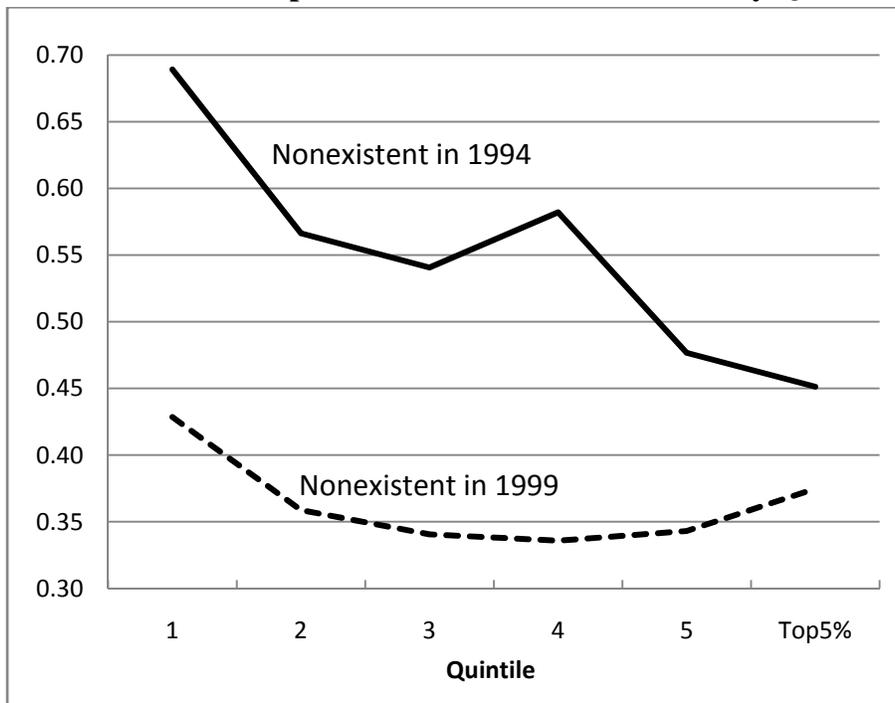
Figure 6: Food Share in ACNielsen Sample

Food Share in NonDurable Sample
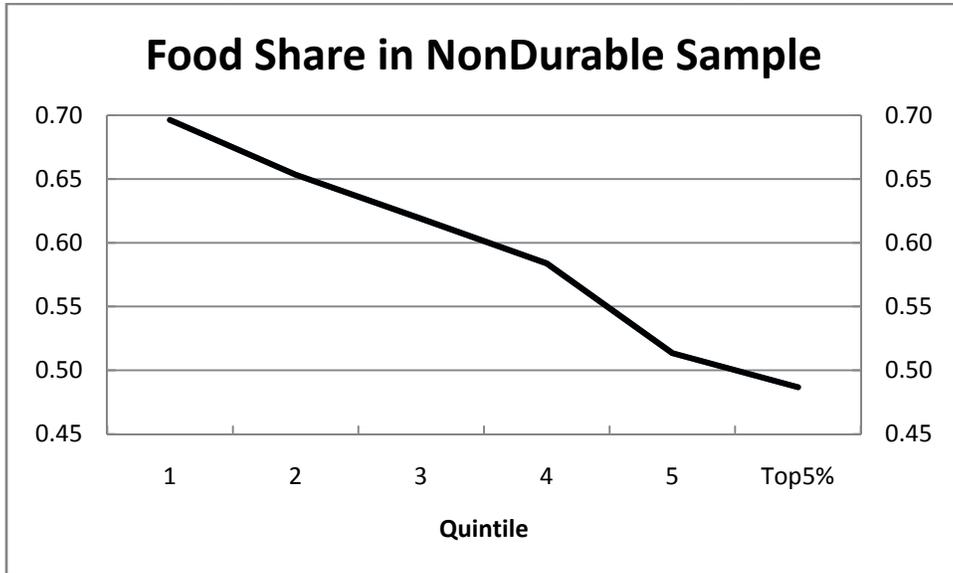
Figure 7A: Food Inflation Rate by Percentile 1994-2005
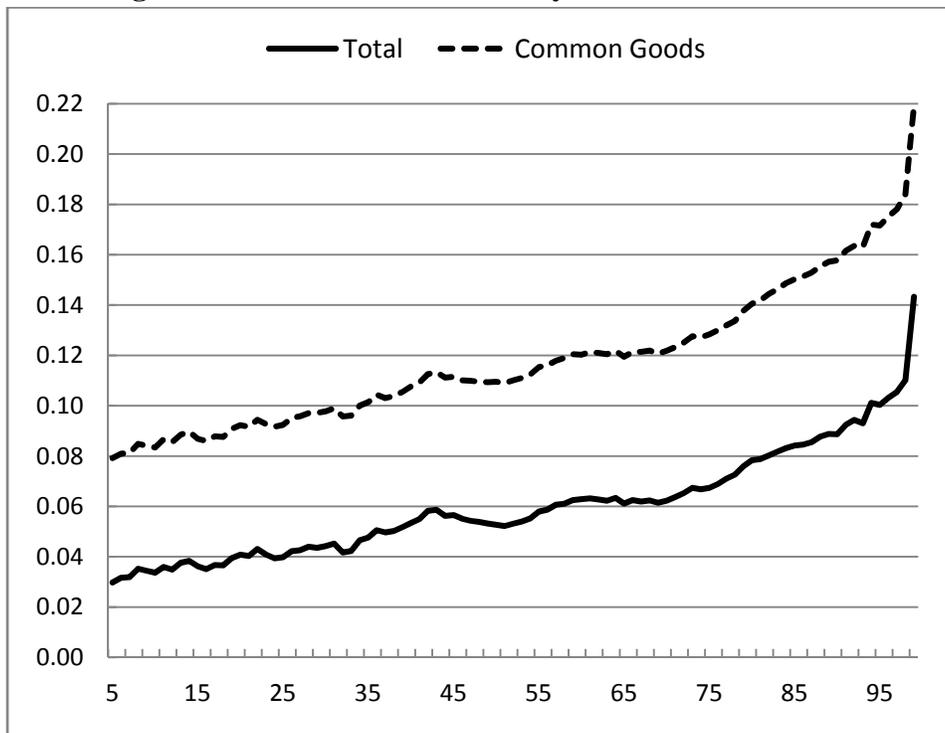
Figure 7B: Non-Food Inflation Rate by Percentile 1994-2005

Figure 7C: Cost of Living Index for Entire Sample by Percentile, 1994-2005

Figure 8: Household Income and Welfare Distribution: 1994 and 2005
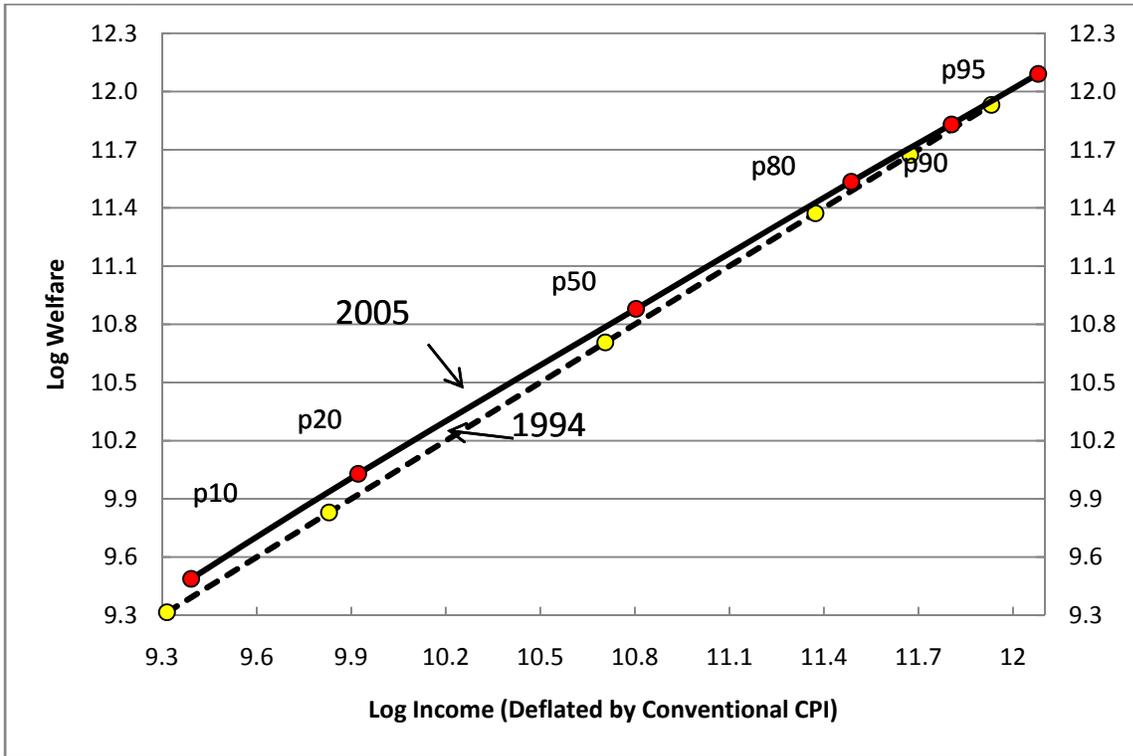
Figure 9A: Rising Price Dispersion for Food UPCs
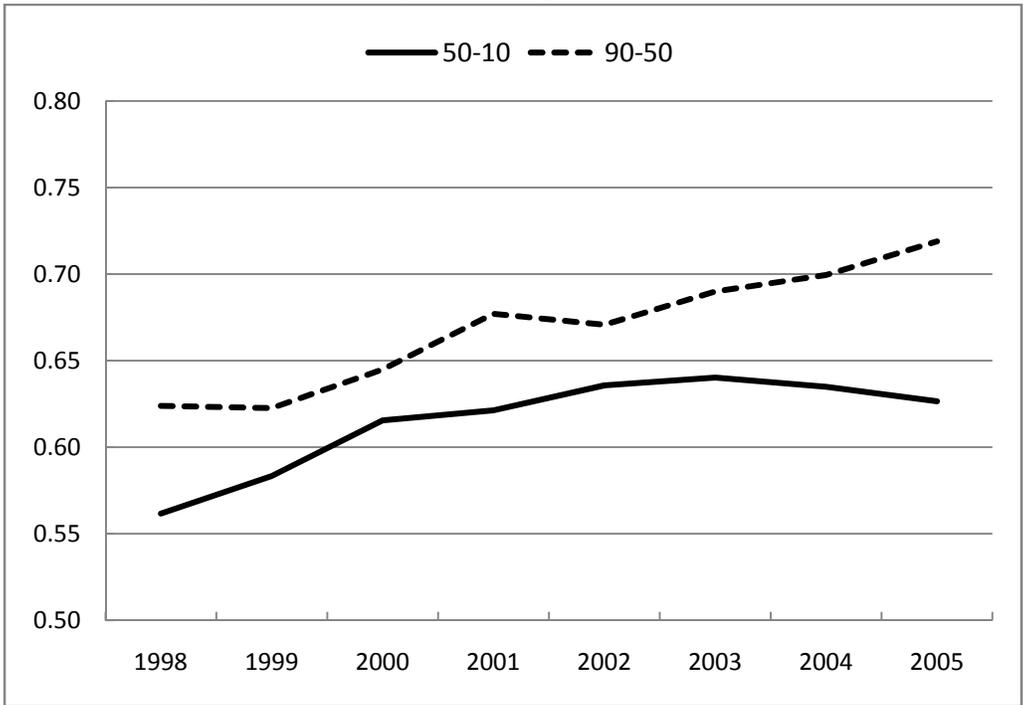
Figure 9B: Rising Price Dispersion for Non-Food UPCs
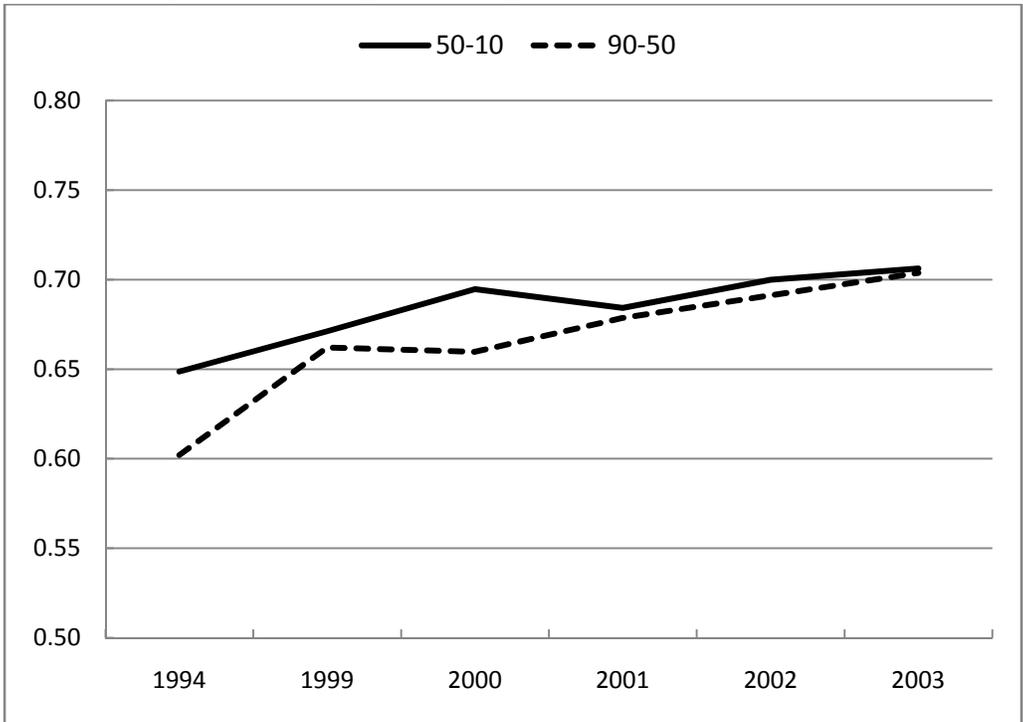
Figure 10A: Shopping for Food at Walmart by Quintile
Share of Food Expenditure
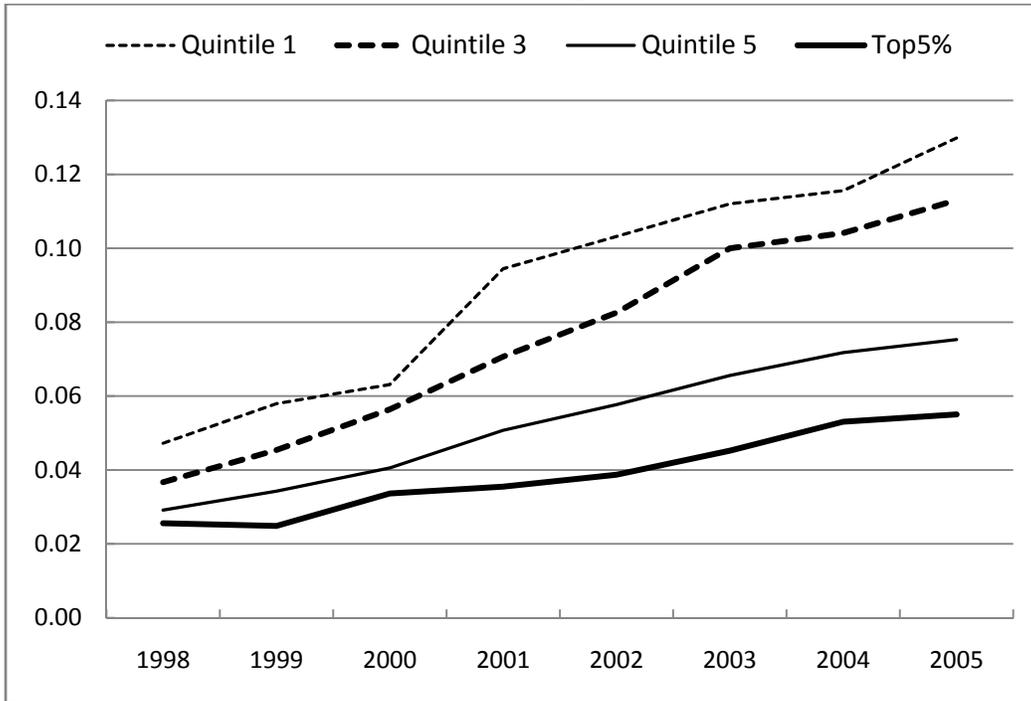
Figure 10B: Shopping for Food at Wholefoods by Quintile
Share of Food Expenditure
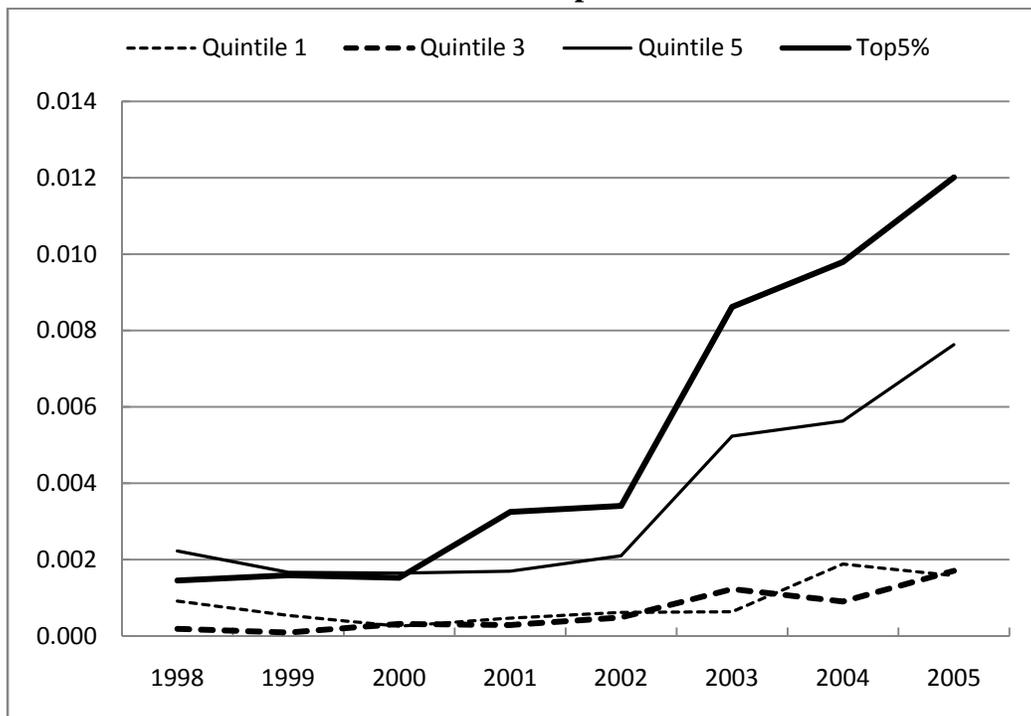
Figure 11A: Laspeyres, Paasche and Sato-Vartia Price Indexes by Percentile for Food 1998-2005
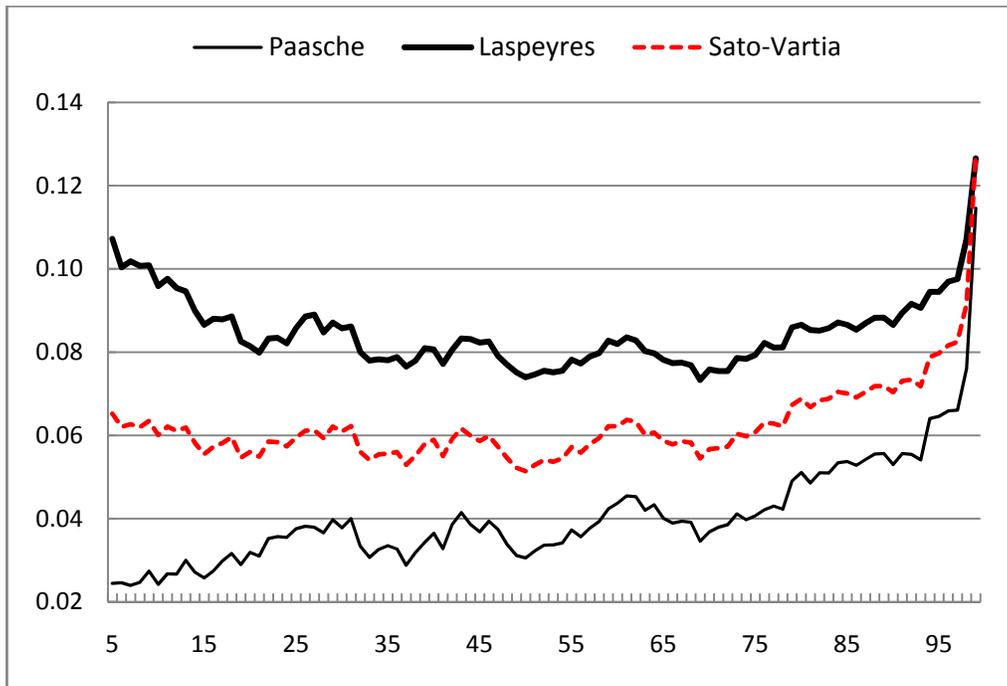
Figure 11B: Fisher and Sato-Vartia Price Indexes by Percentile for Food 1998-2005
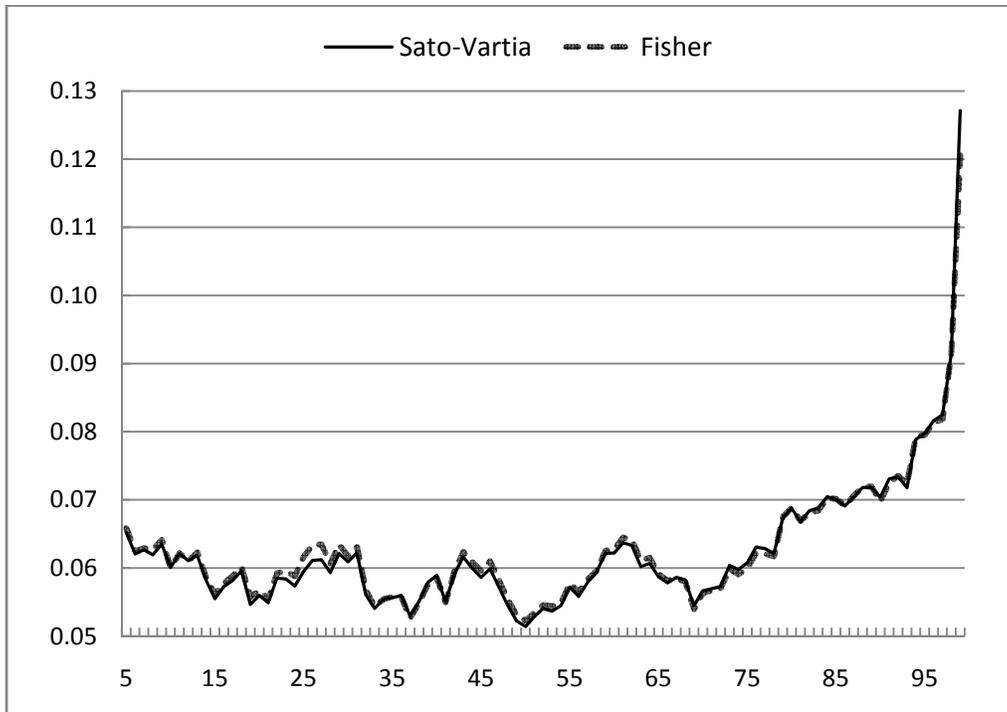
Figure 12: Food Price Inflation by Percentile Applying Income-Specific Weights to Price Indexes for 640 Food Categories 1994-2005
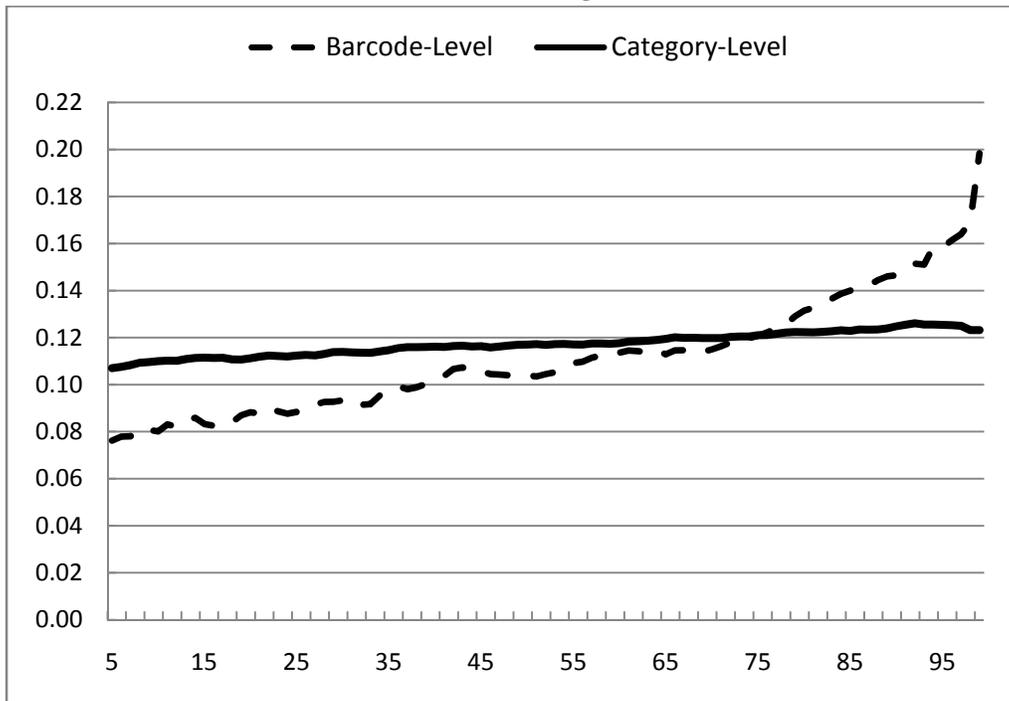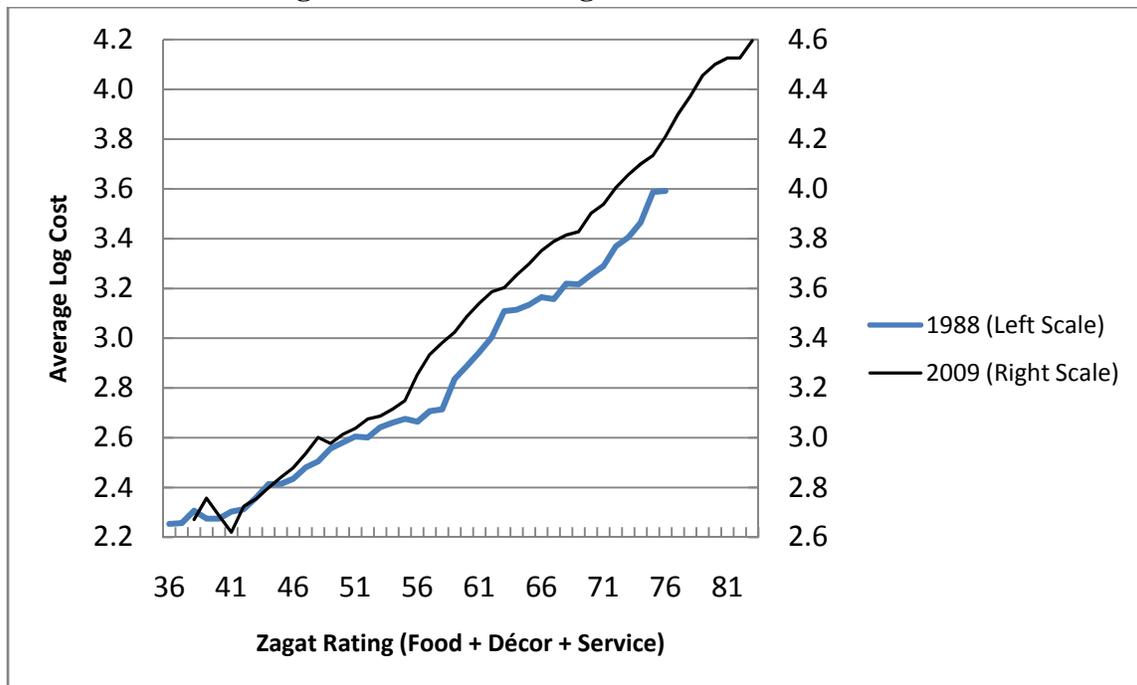

Figure 13: Prices of Zagat-Rated Restaurants

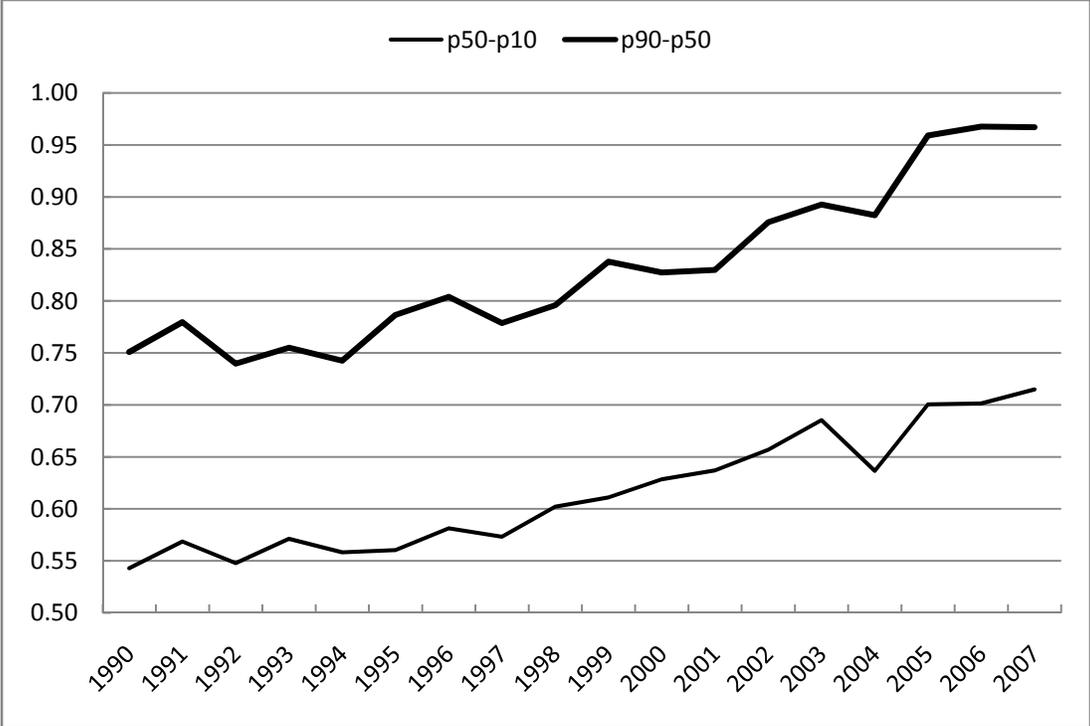**Figure 14: Rising Price Dispersion For US Textile, Clothing and Footwear Imports**

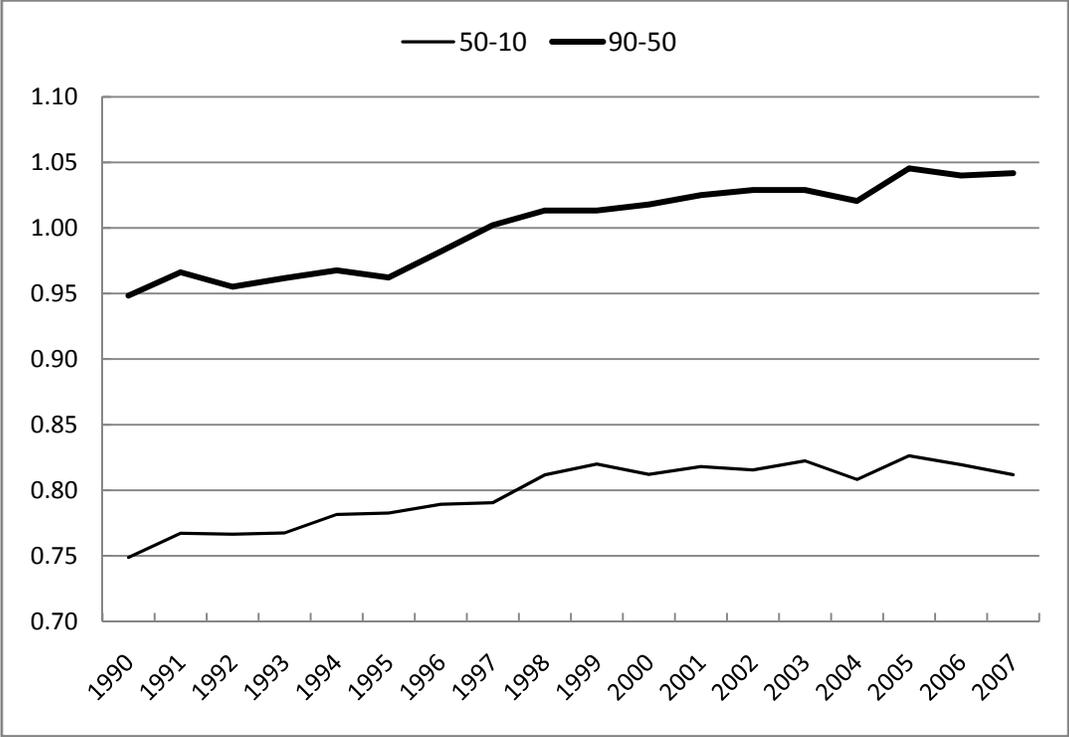**Figure 15A: Rising Price Dispersion for All US Imports 1990-2007**

Figure 15B: Rising Price Dispersion for All US Imports 1972-1988