Price Heterogeneity and Consumption Inequality*

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Abstract

Measures of consumption inequality are often derived from data on expenditures rather than consumption itself. We document that households systematically pay different prices for identical products, and that this price heterogeneity is closely related to household income: lower-income households pay lower prices than higher-income ones for the same product. Such heterogeneity might have a considerable impact on the measurement of consumption inequality: if poor households pay lower prices than rich households, existing measures of nominal consumption inequality may be biased upwards. However, we provide empirical evidence that price heterogeneity does not matter for the measurement of consumption inequality; in other words, we do not find evidence of a significant discrepancy between nominal and real inequality.

Keywords: Consumption Inequality, Price Heterogeneity, Nielsen Consumer Panel

JEL Codes: E21, E31, D20, C30

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1 Introduction

Using the Nielsen Consumer Panel dataset (NCP), we document significant price heterogeneity in the United States. A household in the bottom income quintile on average pays 4 percent less than a household in the top quintile for nearly identical products and up to 20 percent less if we aggregate products into coarser categories. Our results are consistent with the findings of Broda, Leibtag and Weinstein (2009), who worked with 2005 NCP data on food products at the barcode level. We extend their analysis by including nonfood products, investigating explanations for price heterogeneity at the barcode level, and working at different levels of product aggregation. We show that the price differentials are mainly due to the type of supermarket visited and the frequency of shopping.[1]

We then investigate whether the measurement of consumption inequality is influenced by these systematic differences in prices. We compare nominal consumption inequality with an adjusted consumption inequality in real terms: we assign the same prices to the same products and recalculate household annual expenditure, using barcode-level as well as broader definitions of products. This is purely a measurement exercise, as we are not interested in how consumers would react to facing the same prices. The purpose is to go from nominal expenditure inequality to real consumption inequality by removing the price heterogeneity that is not due to quality differences.

We find that the adjustment from nominal to real decreases measured inequality very little. We interpret this as evidence that consumption inequality depends almost exclusively on the quantity and quality of what is consumed, and not its price. If correcting for price heterogeneity does not have a significant impact, most of the inequality must be due to either households consuming different products – which we label *composition heterogeneity* – or households consuming different quantities of the same products, *quantity heterogeneity*. We quantify the contribution of each to consumption inequality and find that the latter plays a bigger role, especially at higher levels of product aggregation.

The NCP only covers a fraction of total household consumption, so it cannot provide a reliable measure of overall consumption inequality. Nevertheless, it provides an excellent setting in which to study price heterogeneity, as price discrimination is widely practiced in retail. Moreover, the dataset offers a unique opportunity to investigate the impact of price heterogeneity on the measurement of consumption inequality because it includes information on prices and quantities separately, thus allowing us to move from nominal to real inequality. Following the same logic, Coibion, Gorodnichenko and Koustas (2021) recently used data from the NCP to study the impact of the decline in the frequency of shopping on consumption inequality; the NCP includes expenditure for each shopping trip, which allowed the

[1] Consumption is usually measured using surveys on household expenditures. Aguiar and Hurst (2005) were the first to find significant differences between household expenditure and household consumption, as time invested in the search for lower prices crucially depends on the age, income, and education of households.

authors to evaluate the sensitivity of measuring inequality at different frequencies of aggregation of consumption expenditures. Finally, recent papers, such as Argente and Lee (2021) and Handbury (2021), use the NCP dataset to study the welfare implications of variation in cost of living across time and space; our results shed light on the relevance of price heterogeneity for the measurement of inequality within the Nielsen data and are therefore informative on the link between this recent strand of literature and the measurement of consumption inequality.

Several papers have documented significant variation in the prices paid by consumers for a given product, such as Handbury and Weinstein (2015) and Kaplan and Menzio (2015). We are especially interested here in showing that low-income households pay lower prices for the same products, which was first documented by Broda, Leibtag and Weinstein (2009) using data from Nielsen. To the best of our knowledge, we are the first to jointly use four different levels of product definition to study price heterogeneity: the barcode level, which includes about two million products in our dataset; the brand-module level, which aggregates barcode-level products to around 235,000 units; the module level, which aggregates products to about 1,500 units; and finally, the group level, which aggregates products to around 200 units. The brand-module category is the closest to how an economist would define a product, but the module and group levels of aggregation are also worth considering, as they completely abstract from potentially economically irrelevant marketing distinctions between products, albeit at the cost of hiding potentially significant quality differences.

Recent academic literature has shown considerable interest in measuring the level and trend of inequality of income, consumption, wages, and other indicators of household resources and welfare. Piketty and Saez (2003) present striking evidence that income inequality has been increasing in the past century in the United States. Similarly, Autor, Katz and Kearney (2008) show that wage inequality has risen substantially in recent decades. More controversial is the claim that consumption inequality exhibited a similar trend. Attanasio, Hurst and Pistaferri (2014), Attanasio and Pistaferri (2014), and Aguiar and Bils (2015) find that consumption inequality has increased over time in the same way as income inequality, once measurement-error issues are addressed; on the other hand, Coibion, Gorodnichenko and Koustas (2021) find that the measured rise in consumption inequality since the 1980s has been mostly due to a decline in shopping frequency, which has led to an increasing upward bias in the measurement.

Our findings for consumption inequality are different from those of Moretti (2013) on wage inequality. He shows that skilled workers since 1980 have disproportionately concentrated in cities with increasingly higher costs of living and therefore experienced higher price inflation than unskilled workers, suggesting that wage inequality has grown less in real than nominal terms. Also using Nielsen data, Argente and Lee (2021) construct income-specific price indexes and find substantial differences in price inflation across income groups during the Great Recession. We do not explicitly look at trends in our data, but our repeated cross-sectional analysis does have implications for the dynamics of inequality: if real expenditure inequality grew much less than nominal expenditure inequality in our database, we would observe a significant discrepancy between nominal and real measures of inequality, especially toward the end of our sample.[2]

2 Data description

Our primary source of data is the Nielsen Consumer Panel (NCP). It is a longitudinal survey that covers the day-to-day grocery purchases of 40,000 to 60,000 households, depending on the year.[3] Each panelist is equipped with an in-home scanner to record their purchases of all Nielsen-tracked products from many retail outlets in the United States. These retail outlets include, among others, supermarkets, discount stores, drug stores, liquor stores, coops, and home-delivery outlets. Nielsen attempts to keep the panel geographically and demographically balanced and provides demographic weights for each household to make the sample representative at the national and regional levels. Broda and Parker (2014) report that spending per capita in the NCP is about 10 percent of NIPA per capita Personal Consumption Expenditures (PCE), and household spending is around 35 percent of spending on nondurable goods in the Census Consumption Expenditure Survey (CEX). Moreover, they report that the NCP covers around 40 percent of all expenditures on goods in the Consumer Price Index (CPI).

Our sample covers 8 years of NCP data from 2008 to 2015 and records approximately 40 million transactions from an average of 5 million shopping trips per year. Each observation represents the purchase of a barcode-level product and is associated with information on both the product and the outlet: price, quantity purchased, retailer type, location, and physical product characteristics such as size and unit of measurement. The dataset also provides demographic information on the households participating in the panel – for instance, number of adults and children, age, education level of the head of household, marital status, occupation, and binned household income.[4] Following the literature, we drop households whose head is younger than 25 or older than 65 years old. We also eliminate households with size equal to or higher than 9, as we are unable to observe the precise size of those households. We also exclude from the sample purchases of products with nonstandard barcodes ("magnet goods") which may be assigned to different products by different outlets, such as random-

[2] Jaravel (2019) also uses the NCP and finds that higher-income households benefited more from product innovation and experienced a lower inflation rate for continuing products over the past decade, which is consistent with our results and overturns the evidence presented by Broda and Romalis (2009).

[3] We consider as *groceries* all packaged consumer products intended for personal, in-home use, irrespective of the outlet they are purchased from. They include both food and nonfood items that one could expect to find in a grocery store, including fresh and dry food, personal care products, household consumables, alcoholic beverages, and nonprescription drugs.

[4] We restrict our analysis to the period 2008-15 because in these years the household income bins provided by Nielsen can be used to construct quintile income dummies that are consistent with the Census thresholds for income quintiles.

weight fruits, vegetables, meats, and store-baked goods. We also remove records most likely arising from misreporting, such as those with nonpositive quantity, nonpositive net-of-discount price, or missing information.

The barcode-level product definition is the most detailed product definition in our dataset, and it perfectly identifies the products that are sold by a vendor by their Universal Product Code (UPC). However, the same type of product will be sold in different packaging options, and each will have a different UPC number (for instance, a single soda, a 6-pack, and a 12-pack will have three different UPCs even though they are the identical product in different quantities). The brand-module product definition was introduced by Handbury and Weinstein (2015) to identify products independently of the packaging. We also consider coarser product definitions: the module and group levels provide wider product definitions that aggregate different brands. For instance, cracker is a product group that is divided into five modules: flaked soda, flavored snack, graham, oyster, and remaining. Within modules and groups, there might be significant quality differences, but the product definition is guaranteed to abstract from irrelevant marketing characteristics. We create these product definitions relying on Nielsen's product categories and some product characteristics such as unit size and brand.[5]

The main variables of interest in our analysis are the quantities purchased and prices paid for each product. Prices are collected in two different ways: First, when the panelist inputs a purchase in their scanner, if the store provides Point-of-Sale (POS) data to Nielsen, the price of the product is imputed by the company as the average weighted price for the item during that week in that particular store. Second, if the store where the product was purchased does not provide POS attributes, the panelist is instructed to enter the price paid, prior to any coupons or deals. The panelist is then prompted to input any discount or coupon value in the scanner. Following previous literature, we compute the product price as the difference between the purchase price and the discount.

There are two ways to compute consumption expenditures with the NCP dataset. For each trip to a store, the panelist first inputs the total amount spent on the trip and then separately inputs the expenditure on each product purchased. Einav, Leibtag and Nevo (2010) note that the expenditures on all products purchased on a trip often do not sum up to the total amount spent reported for that trip. This discrepancy is partially due to taxes, which are included in the total amount spent but not in the prices reported for each product. However, taxes cannot explain all the gap, which means that panelists most likely neglect to report the purchase of some products.[6]

[5]For instance, we divide some Nielsen modules that contain products with different unit sizes to make it possible for us to compare their prices. As a consequence, our definitions of module and group do not precisely coincide with Nielsen's.

[6]We investigate this discrepancy in Section A.1 of the Online Appendix. Figure A1 in the Online Appendix shows mean annual consumption measured in both ways with Nielsen data, along with corresponding Census CEX data. Table A1 shows that household income level does not statistically explain much of the variation in the discrepancy between the two measures.

More generally, several studies have assessed the reliability and representativeness of the NCP relative to comparable data sources, such as POS records or expenditure surveys administered by statistical offices. Einav, Leibtag and Nevo (2010) report that household-reported prices are significantly noisier than their POS counterparts, but they also show that this measurement error is likely to bias downward the coefficient of income in a price regression.[7] Relatedly, Aguiar and Hurst (2007) show that demographics of Nielsen panelists are in line with estimates from the Panel Study of Income Dynamics.[8]

Also note that the NCP only includes households that report purchases for at least 10 months of the year; their data are generally considered more reliable than the data of those who report for fewer months.

3 Price heterogeneity

To begin, we aim to provide evidence on the average log unit price paid by a household in a quarter for a product, regressed on income-quintile dummies, demographic controls, and product, geographical and time fixed effects. Formally, our empirical specification is as follows:

$$\bar{p}_{ij}^{t} = \alpha + Y_j^t \beta + X_j^t \gamma + \mu_i + \tau_t + \varepsilon_{ij}^t \tag{1}$$

Here, $\bar{p}_{ij}^{t}$ is the log of the average unit price paid for product i by household j during quarter-year t; Y_j^t is a set of income-quintile dummies (top quintile is excluded); X_j^t is a set of demographic characteristics, including age of the head of the household, household size, and geographic location; μ_i are product fixed effects; τ_t are quarter-year fixed effects; finally, ε_{ij}^t is an idiosyncratic error term, which we allow to be correlated within the same household. β is our vector of coefficients of interest. Our geographical market definition is based on Core-Based Statistical Areas (CBSAs).[9]

We estimate equation (1) at each of the four product-definition levels. Table 1 shows that poor households pay lower prices for the same products at all levels of product definition. We find a similar degree of price heterogeneity at the barcode (UPC) level to that found by Broda, Leibtag and Weinstein (2009), who ran similar regressions using only food items at the barcode level with the 2005 NCP dataset. At the brand-module level, bottom-quintile households pay about 3.6 percent less than top-quintile households. At the more aggregated levels (module and group), the poor pay on average around 15–20 percent less, but quality differences are likely driving some of the price differentials.[10]

[7]In addition, they document that errors are comparable to what is found in other commonly used datasets, and that data on quantities are much more reliable.

[8]For a detailed comparison of NCP and CEX, see Zhen et al. (2009).

[9]CBSAs – defined by the Office of Management and Budget – are clusters of counties tied to an urban center by commuting patterns. Households that do not reside in CBSAs are not included in the sample of the regressions in Tables 1 and 2. About 40,600 households are included on average per year.

[10]Section A.3 in the Online Appendix shows that the price heterogeneity found in Table 1 exists across product categories and years and is robust to using frequency and expenditure weights.

Table 1: PRICE HETEROGENEITY ACROSS PRODUCT CATEGORIES

Product def.	UPC	Brand-module	Module	Group
Lowest	–1.27	–3.64	–13.81	–17.10
	(0.18)	(0.22)	(0.30)	(0.34)
Second	–1.80	–3.68	–11.68	–14.25
	(0.16)	(0.19)	(0.26)	(0.29)
Third	–2.07	–3.48	–9.31	–11.27
	(0.15)	(0.18)	(0.25)	(0.28)
Fourth	–1.54	–2.39	–5.69	–6.88
	(0.13)	(0.16)	(0.22)	(0.24)
Adj. R^2	0.86	0.89	0.81	0.69
Within R^2	0.001	0.001	0.006	0.005
F-stat	55.38	125.60	782.00	994.40
Observations	226,458,924	182,925,772	131,434,040	72,624,040

NOTES: Percentage change in prices for same product as a function of income quintile (top quintile excluded). Percentage change computed as (100*exp(β)-1). *Dependent variable:* log pretax unit price (net of coupons) paid on average by a given household for product (identified at different levels) during quarter-year. *Controls:* fixed effects for age of the head of household, household size, quarter-year, CBSA, and product. All regressions include a constant. Standard errors are clustered at the household level in parentheses. The within R^2 reports the fraction of variation explained by income-quintile dummies, conditional on controls and fixed effects. Regressions are precision weighted with sampling weights provided by Nielsen. *Sample:* Nielsen Consumer Panel dataset, years 2008-15.

In Table 2, we investigate the reasons for the price differentials found in Table 1. We first compute for each family in the dataset the log average number of shopping trips per week and the fraction of the expenditure associated with the use of a deal, a coupon, a purchase made at a big-box store (for example, Walmart) or warehouse club (for example, Costco), or a purchase of a large item.[11] We then regress these quantities on income dummies and other controls: age of the head of household, household size, quarter-year, and CBSA fixed effects. We find little difference between rich and poor households in the use of deals, coupons, and large items, but lower-income households take more shopping trips, which is consistent with a higher intensity in the search for lower prices. Moreover, poor households spend about 8 percent more than rich households in big-box stores, whereas they appear to be less likely to shop at warehouse clubs.

4 A decomposition of consumption inequality

We now propose a decomposition of consumption inequality that will help us uncover its main drivers. We start with some definitions. If household i consumes quantity x of product m, we denote it by x_{im}. N is the number of households in the sample; M is the set of available products and M_i the set of products that household i purchases; $x_{im} > 0$ if $m \in M_i$ and $x_{im} = 0$ if $m \in M_i^c$, where $M_i^c = M \backslash M_i$. The price of product m paid by household i is p_{im}. The average price for product m across the economy is $\bar{p}_m = \frac{\sum_i x_{im} p_{im}}{\sum_i x_{im}}$. The average quantity purchased of product m across the economy is $\bar{x}_m = \frac{1}{N} \sum_i x_{im}$.

[11] We follow Nevo and Wong (2019) and define large items as UPC products that rank in the top 40 percent of the size distribution within each module. We use Nielsen's categorization of stores to identify big-box stores and warehouse clubs.

Table 2: FRACTION OF EXPENDITURES

	Deal	Coupons	Big-box stores	Warehouse clubs	Large item	Frequency
Lowest	−4.52	−2.62	8.12	−8.75	−2.02	10.70
	(0.36)	(0.20)	(0.64)	(0.31)	(0.19)	(1.11)
Second	−2.33	−1.76	7.43	−7.53	−1.82	12.30
	(0.31)	(0.17)	(0.39)	(0.31)	(0.15)	(0.93)
Third	−0.73	−0.73	5.61	−5.55	−1.36	8.10
	(0.33)	(0.17)	(0.42)	(0.30)	(0.17)	(0.94)
Fourth	0.32	−0.06	3.32	−3.00	−0.66	4.66
	(0.36)	(0.14)	(0.29)	(0.25)	(0.12)	(0.68)
Adj. R^2	0.07	0.05	0.21	0.11	0.06	0.08
Within R^2	0.00	0.01	0.01	0.03	0.00	0.00
F-stat	75.59	69.75	91.88	229.19	44.23	45.21
Observations	1,299,519	1,299,519	1,299,519	1,299,519	1,299,519	1,299,521

NOTES: The dependent variable is the fraction of expenditure with deals (second column), with coupons (third column), in big-box stores (fourth column), in warehouse clubs (fifth column), and on large items (sixth column) by a given household, per quarter-year. The dependent variable in the last column is the (log) number of trips by a given household within a quarter-year. Coefficients shown refer to income quintiles (top quintile excluded, figures in percentages). *Controls:* fixed effects for age of the head of household, household size, quarter-year, and CBSA. All regressions include a constant. Robust standard error are clustered at the CBSA level and reported in parentheses. Figures are computed using sampling weights provided by Nielsen. *Sample:* Nielsen Consumer Panel dataset, years 2008-15.

The difference between household i's expenditure and the expenditure of the average consumer, who pays the average price and buys the average quantity of each product, can be decomposed into two factors as follows:

$$\sum_{m\in M} p_{im}x_{im} - \sum_{m\in M} \bar{p}_m\bar{x}_m = \underbrace{\sum_{m\in M} (p_{im} - \bar{p}_m)x_{im}}_{\text{Price heterogeneity}} + \underbrace{\sum_{m\in M} \bar{p}_m(x_{im} - \bar{x}_m)}_{\text{Inequality in real terms}} \tag{2}$$

The first term on the right-hand side highlights price heterogeneity. The larger the differences between the prices paid by a household and the average prices, the larger the difference between the household's expenditure and the average consumer's expenditure, $\sum_{m\in M} \bar{p}_m\bar{x}_m$. The second term is due to differences in quantities consumed.

Naturally, households only consume a fraction of the products available. For this reason, the quantity differences in (2) are in part due to the lack of consumption of some products. In other words, the difference between household i's expenditure and the average consumer's expenditure is due to two factors: the household does not consume certain products at all, and the household consumes some products in a different quantity than the average consumer. We now further decompose the second term in (2) to reflect these two factors, which we will call *composition heterogeneity* and *quantity heterogeneity*. For instance, say there are three products in the economy: potatoes, steaks and apples. The average person consumes 2 potatoes, 2 steaks, and 2 apples. Paul consumes 0 potatoes, 1 steak and 3 apples. The difference between Paul and the average consumer is that Paul consumes fewer steaks and more apples than the average person and also that he is not consuming potatoes at all. Formally, we further decompose the second term on the right-hand side of (2) as follows:

$$\sum_{m\in M}\bar{p}_m(x_{im}-\bar{x}_m)=\underbrace{\sum_{m\in M_i}\bar{p}_m(x_{im}-\bar{x}_m)}_{\text{Quantity heterogeneity}}+\underbrace{\sum_{m\in M_i^c}\bar{p}_m(0-\bar{x}_m)}_{\text{Composition heterogeneity}} \tag{3}$$

Having established some definitions, we can now talk about consumption inequality. Following the previous literature, we divide household consumption by the OECD adult-equivalence scale, S_i. We define $\hat{x}_{im}=\frac{x_{im}}{S_i}$ and $\tilde{x}_m=\sum_i\frac{\hat{x}_{im}}{N}$, and we measure inequality (denoted as $\mathcal{I}$) as the standard deviation of total annual expenditure:

$$\mathcal{I}=\sqrt{\frac{1}{N-1}\sum_i\left(\sum_{m\in M}p_{im}\hat{x}_{im}-\frac{1}{N}\sum_i\sum_{m\in M}p_{im}\hat{x}_{im}\right)^2} \tag{4}$$

To assess the importance of price heterogeneity, we first impose $p_{im}=\bar{p}_m$. We are then left with

$$\mathcal{I}=\sqrt{\frac{1}{N-1}\sum_i\left(\sum_{m\in M}\bar{p}_m\hat{x}_{im}-\frac{1}{N}\sum_i\sum_{m\in M}\bar{p}_m\hat{x}_{im}\right)^2}=\sqrt{\frac{1}{N-1}\sum_i\left(\sum_{m\in M}\bar{p}_m(\hat{x}_{im}-\tilde{x}_m)\right)^2}. \tag{5}$$

We look at the ratio of (5) to (4) to measure the importance of price heterogeneity in the measurement of consumption inequality. The lower the ratio, the lower the consumption inequality when measured in real terms – that is, with the same fixed prices for all consumers. In contrast, the closer the ratio is to one, the weaker is the impact of price heterogeneity on the measurement of inequality.

After we control for price heterogeneity, consumption inequality reduces to the second term on the right-hand side of (2), adjusted with the adult-equivalence scale. Following (3), we can further decompose the remaining consumption inequality into quantity and composition heterogeneity:

$$\begin{aligned}\mathcal{I}&=\sqrt{\frac{1}{N-1}\sum_i\left(\sum_{m\in M}\bar{p}_m(\hat{x}_{im}-\tilde{x}_m)\right)^2}\\&=\sqrt{\frac{1}{N-1}\sum_i\left(\sum_{m\in M_i}\bar{p}_m(\hat{x}_{im}-\tilde{x}_m)+\sum_{m\in M_i^c}\bar{p}_m(0-\tilde{x}_m)\right)^2}\end{aligned} \tag{6}$$

We then measure the importance of quantity and composition heterogeneity with the share of consumption inequality due to pure quantity heterogeneity,

$$\mathcal{S}_q = \frac{\sqrt{\sum_i \left(\sum_{m \in M_i} \bar{p}_m(\hat{x}_{im} - \tilde{x}_m)\right)^2}}{\sqrt{\sum_i \left(\sum_{m \in M} \bar{p}_m(\hat{x}_{im} - \tilde{x}_m)\right)^2}}, \tag{7}$$

and the share of consumption inequality due to composition heterogeneity,

$$\mathcal{S}_c = \frac{\sqrt{\sum_i \left(\sum_{m \in M_i^c} \bar{p}_m(0 - \tilde{x}_m)\right)^2}}{\sqrt{\sum_i \left(\sum_{m \in M} \bar{p}_m(\hat{x}_{im} - \tilde{x}_m)\right)^2}}. \tag{8}$$

Finally, there might be a nonzero covariance between quantity and composition heterogeneity (Q and C respectively):

$$Cov(Q, C) = 2\sum_i \left[\sum_{m \in M_i} \bar{p}_m(\hat{x}_{im} - \tilde{x}_m) \cdot \sum_{m \in M_i^c} \bar{p}_m(0 - \tilde{x}_m)\right] \tag{9}$$

5 Does price heterogeneity matter?

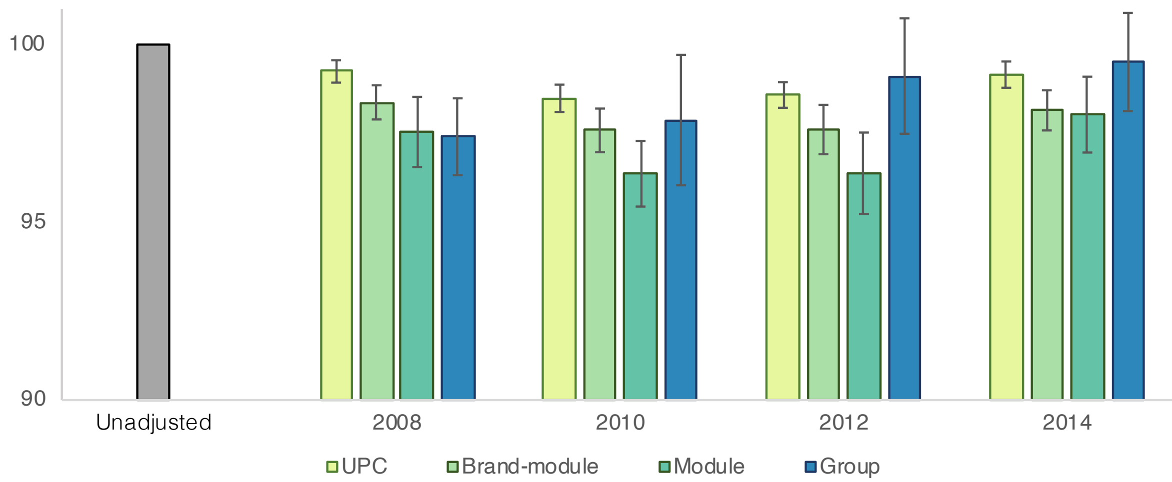
We now address our main research question: does price heterogeneity meaningfully affect the measurement of consumption inequality? As explained in the previous section, we compare consumption inequality measured at actual prices and consumption inequality measured with the same prices for all consumers. We first compute the average price paid for each product in the United States during each year. We then use this average price to compute a price-adjusted measure of annual household expenditure, which is one that abstracts from price heterogeneity across income quintiles. Finally, we compute consumption inequality as the standard deviation of annual consumption adjusted with the adult equivalence scale. We implement this procedure for each of the four levels of product-definition levels described in Section 3.

Figure 1 reports the ratios of (5) to (4) in percentages for a few selected years.[12] We find that adjusted inequality is on average 1 percent lower than observed inequality at market prices when the adjustment is made at the barcode level and no more than 4.75 percent lower when the adjustment is made at broader product-definition levels. We interpret these results as suggesting that price heterogeneity has a very small impact on the measurement of consumption inequality. The coarser product categories might hide quality differences, but some of these differences might be irrelevant for the measurement of welfare inequality. In other words, even if we assume that barcode-level items in the same module – for instance, different types of cheese crackers – are in fact the same product from the consumer's

[12] The results for all years can be found in Table A13 in the Online Appendix.

perspective, we still find that real and nominal inequality are nearly identical, despite large price differentials by income bracket. These results are robust to measuring inequality in different ways, such as the interquartile range, 90-10 ratio, 90-50 ratio, and 50-10 ratio, as shown in Section A.4.1 in the Online Appendix. They are also reasonably tightly estimated and stable over time.[13]

Figure 1: CONSUMPTION INEQUALITY ADJUSTMENT



NOTES: Unadjusted inequality computed as standard deviation of consumption expenditures and reported as 100%. Adjusted consumption inequality is computed as a percentage of actual consumption inequality, for different product definitions. Nonparametric bootstrap standard errors reported as error bars (500 replications). Figures are computed using sampling weights provided by Nielsen and adjusted using the adult-equivalence scale. Additional years and figures are reported in Table A13 in the Online Appendix.

Many papers have looked at changes and trends in inequality, and some, such as Moretti (2013), link them to diverging inflation rates for rich and poor. Figure 1 shows that there is no trend in the contribution of price heterogeneity to consumption inequality in the studied period. Moreover, since the contribution is small at the end of the sample, we can reject the hypothesis that real expenditure inequality has grown much less than nominal expenditure inequality in the decades preceding our sample.

Two factors that we cannot control for might be biasing our results. First, higher-income people are more likely to use credit cards for payment and participate in rewards programs, such as travel points, which might somewhat reduce the effective price they pay. Moreover, lower-income households must incur some costs to seek lower prices, which increases to some extent the effective prices they face. Both of these phenomena bias the ratios in Figure 1 downward; our results can therefore be seen as an upper bound on the difference between nominal and real inequality.

[13]Standard errors are computed following the nonparametric bootstrap procedure described in Efron and Tibshirani (1993), p. 47. For each year, we sample with replacement from the set of households of the NCP dataset until we match the number of households in the original sample. Then we match the corresponding transactions and aggregate products according to their definition. In the next step, we compute the average price paid in the bootstrap sample for each product and compute adjusted and unadjusted measures of consumption inequality. The ratio of these two measures constitutes our bootstrap replication. After repeating this procedure 500 times, we estimate the standard error as the standard deviation of these replications.

5.1 Quantity versus composition heterogeneity

If price heterogeneity does not matter for consumption inequality, it must be that quantity and composition heterogeneity explain almost all of the inequality in the data. We now decompose consumption inequality into its quantity and composition components, as explained in Section 4. Table 3 reports the measures of the relative importance of quantity and composition heterogeneity described in (7) and (8). Quantity and composition heterogeneity are both very important in explaining consumption inequality, and they appear to be strongly negatively correlated, as the sum of the ratios (7) and (8) is always above unity. Intuitively, as the product definition becomes wider and the total number of products decreases, the importance of composition heterogeneity decreases as well. At the group level, most consumption inequality is due to quantity heterogeneity, which is what we would expect for such a broad definition level. As with Figure 1, the results in Table 3 are stable over time.

Table 3: QUANTITY VS. COMPOSITION

	UPC		Brand-Module		Module		Group	
	$\mathcal{S}_q$	$\mathcal{S}_c$	$\mathcal{S}_q$	$\mathcal{S}_c$	$\mathcal{S}_q$	$\mathcal{S}_c$	$\mathcal{S}_q$	$\mathcal{S}_c$
2008	2.07	1.71	1.85	1.48	1.31	0.84	1.03	0.37
2009	2.04	1.66	1.82	1.43	1.31	0.86	1.03	0.37
2010	2.00	1.63	1.78	1.40	1.30	0.82	1.03	0.36
2011	1.99	1.62	1.79	1.39	1.30	0.84	1.03	0.37
2012	1.95	1.57	1.75	1.36	1.28	0.80	1.02	0.35
2013	1.92	1.52	1.73	1.32	1.28	0.79	1.03	0.35
2014	1.94	1.55	1.75	1.35	1.28	0.80	1.03	0.35
2015	1.92	1.54	1.73	1.34	1.27	0.79	1.03	0.35

NOTES: $\mathcal{S}_q$ (equation 7) measures the share of consumption inequality due to quantity heterogeneity and $\mathcal{S}_c$ (equation 8) the share due to composition heterogeneity. Figures are computed with different product definitions using sampling weights provided by Nielsen and adjusted using the adult-equivalence scale. *Sample:* Nielsen Consumer Panel dataset.

6 Concluding remarks

In this paper, we addressed whether inequality in real terms is lower than in nominal terms. Existing evidence, confirmed by our analysis, shows that higher-income households pay lower prices for the same products than lower-income households. We find that the size of the price differential crucially depends on the product definition. The wider the definition, the higher the price gap, but the more the gap can be explained by quality differences.

More importantly, this paper provides evidence on the implications of wage and income inequalities for well-being inequality. We document that price heterogeneity does not matter for the measurement of consumption inequality, independently of how we define a product. Consumption inequality is almost entirely explained by quantity and composition heterogeneity. For this reason, we do not find any evidence that price heterogeneity reduces the impact of rising wage and income inequalities on consumption inequality, as suggested by some recent studies.

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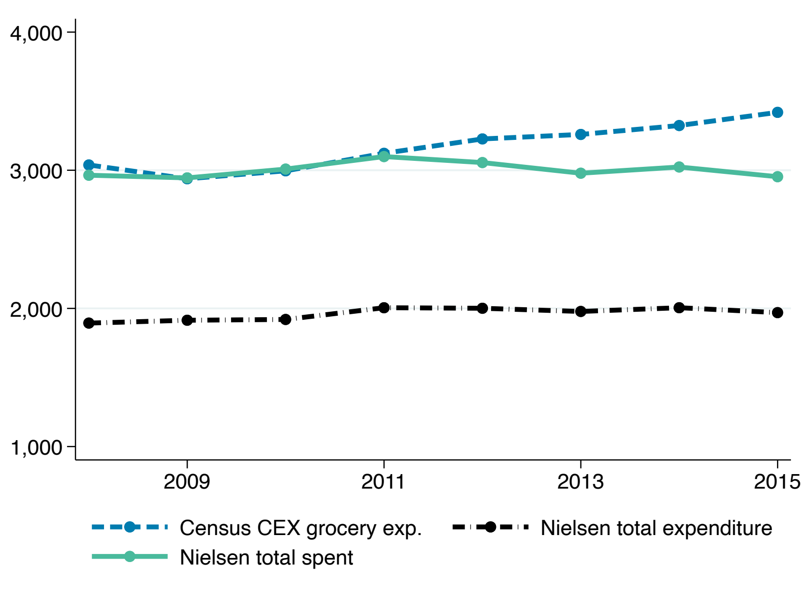
A Online Appendix

A.1 Additional data description

Figure A1: MEAN CONSUMPTION IN CENSUS CEX AND NIELSEN



NOTES: Blue dashed line: grocery expenditures from the Census *Consumer Expenditure Survey*. Black dot-dashed line: average consumption expenditures derived from price and quantity data in the Nielsen Consumer Panel dataset. Green solid line: the equivalent measure declared by the panelist after each shopping run. Figures in U.S. dollars, deflated by implicit price deflator for nondurable goods (FRED series *DNDGRD3Q086SBEA*) and adjusted by adult-equivalence scale.

Figure A1 shows mean annual consumption measured with NCP data and Census CEX data; the black line is computed as the sum of the expenditures on the products purchased, whereas the green line is computed as the sum of the total amount spent on each shopping trip. The weighted averages are computed with the demographic weights provided by Nielsen and Census, and transformed in adult-equivalent terms using the OECD scale.[14] As noted before, household consumption computed summing up all expenditures is lower than when computed using the total amount spent on each trip. The latter tracks well the Census measure, the blue line, whereas the former, which is the measure of consumption we have to use in the main analysis, is about a third lower.[15]

Table A1 shows additional statistics on the ratio of our preferred measure of consumption to the one computed using the total amount spent on each trip. The second column reports for each year the mean ratios for the top income quintile, which hover around 65 percent. Since the reporting rate is lower than 100 percent, it is important to investigate whether it is in any way related to the income of the

[14]The OECD adult equivalence scale is $(1 + 0.7(A - 1) + 0.5K)$, where A is the number of adults and K is the number of children in the household. A child is defined as younger than 18 years old (OECD (2013)).

[15]It must be noted that when using Nielsen data we exclude from the computation of total expenditures what Nielsen calls magnet goods, such as random-weight fruits, vegetables, meats and in-store baked-goods, whereas those products are included in the Census data.

Table A1: HOUSEHOLD REPORTING RATE

Year	Mean of top quintile	*Dep*: Reporting rate Lowest	Second	Third	Fourth	Adj R^2	Obs.
2008	63.20	3.33	2.55	2.07	1.30	0.01	45,240
		(0.35)	(0.35)	(0.35)	(0.35)		
2009	64.31	3.52	2.21	1.84	1.49	0.01	44,026
		(0.33)	(0.33)	(0.33)	(0.33)		
2010	63.22	3.98	2.63	1.85	1.37	0.01	44,006
		(0.32)	(0.32)	(0.32)	(0.32)		
2011	63.89	4.23	2.86	2.55	1.41	0.01	44,097
		(0.34)	(0.34)	(0.34)	(0.34)		
2012	64.51	4.20	2.99	2.70	1.71	0.01	41,992
		(0.32)	(0.32)	(0.32)	(0.32)		
2013	65.76	3.82	2.90	2.41	1.42	0.01	41,813
		(0.31)	(0.31)	(0.31)	(0.31)		
2014	65.35	4.54	3.39	2.91	1.90	0.02	42,140
		(0.28)	(0.28)	(0.28)	(0.28)		
2015	65.74	4.48	3.20	2.70	1.97	0.02	41,715
		(0.27)	(0.27)	(0.27)	(0.27)		

NOTES: The second column reports *total expenditures* as a fraction of *total spent* for the top income quintile (figures in percentages). Columns third to sixth show coefficient estimates of regression of reporting rate on income quintile (top quintile excluded, figures in percentages). All regressions include a constant. Robust standard errors clustered at county level are reported in parentheses. *Sample:* Nielsen Consumer Panel dataset.

households, which might bias the measurement of consumption inequality. For this reason, we report in Table A1 some simple regressions of the reporting rate on income quintile dummies. Lower-income households seem to report a touch more than higher income households, but the difference is not economically significant. Moreover, the low R^2 of the regressions in Table A1 demonstrates that the income level of the household does not statistically explain much of the variation in the reporting ratios. In the next section, Appendix A.2, we report some additional descriptive and demographic statistics.

A.2 Additional Demographics

Figure A2 shows the evolution of consumption inequality in the CEX and NCP. Inequality is measured as the standard deviation of annual household consumption expenditures adjusted with the adult equivalence scale and deflated with the nondurable goods component of the PCE deflator. Inequality measured with the Census CEX data is larger, consistently with average expenditures being higher, as shown in Figure A1, but the two measures are reasonably correlated.

Table A2 shows the frequency of shopping for the households in our dataset for the whole sample and for each income quintile separately. Almost all households shop at least once a month and most of them shop once or twice per week; there do not seem to be significant patterns across income levels. Finally, Table A3 shows that the unweighted NCP is not representative of the U.S. population along the household income dimension. For this reason, throughout the paper we will use the sampling weights

Figure A2: CONSUMPTION INEQUALITY IN CENSUS CEX AND NIELSEN

NOTES: Blue dash line: standard deviation of individual grocery expenditures from Census *Consumer Expenditure Survey*. Green solid line: standard deviation of total expenditures from Nielsen Consumer Panel dataset. Figures in 2012 US dollars, deflated by implicit price deflator for nondurable goods (FRED series *DNDGRD3Q086SBEA*) and adjusted by adult-equivalence scale.

Table A2: FREQUENCY OF SHOPPING

	Lowest	Second	Third	Fourth	Top	All sample	
						Share in %	Obs.
5+ times/week	0.27	0.25	0.16	0.09	0.06	0.14	153
3-5 times/week	4.77	5.16	4.74	4.09	3.81	4.43	4,746
1-2 times/week	60.85	64.03	64.33	64.88	65.36	64.41	69,037
More than once/month	33.88	30.26	30.47	30.74	30.53	30.77	32,984
Less than once/month	0.23	0.30	0.29	0.20	0.25	0.25	270

NOTES: Columns second to sixth report frequency of shopping trips by income quintile. Figures are in percentage points with respect to the total number of trips made by households in each quintile. *Sample:* Nielsen Consumer Panel dataset, years 2008-2015.

provided by Nielsen to make the sample more representative.[16] It must be noted that even using the demographic weights, the NCP data somewhat underrepresents the lowest income quintile.

Table A3: AVERAGE INCOME DISTRIBUTION, IN QUINTILES

Approx. bracket ($)	Nielsen (%)		Census (%)
	Unweighted	Weighted	
Below 19,999	9.1	13.9	20
20,000-39,999	20.8	21.2	20
40,000-59,999	22.0	18.6	20
60,000-99,999	30.6	24.0	20
Above 100,000	17.5	22.3	20
Total	100	100	100

NOTES: The first column reports the approximate brackets for income quintiles in the United States in U.S. dollars (source: U.S. Census Bureau). Columns second and third report the share of households in each bracket with and without the application of the sampling weights provided by Nielsen (figures in percentages). The last column shows the approximate share of each bracket in the U.S population.

[16] Nielsen applies an optimization routine to assign a projection weight to each panelist. The algorithm matches the sample frequencies of nine target demographic factors to the corresponding population values. Details are provided in Muth and Zhen (2007).

A.3 Robustness of price regressions

A.3.1 Price regressions within product categories

We investigate in this section whether the price heterogeneity found in Table 1 varies across products categories. Tables A4-A7 show that the poor systematically pay lower prices across almost all categories of products.[17]

Table A4: PRICE HETEROGENEITY – UPC LEVEL

Product Department	Lowest	Second	Third	Fourth	Adj R^2	Obs.
Panel A						
Candy	−1.35	−1.92	−2.15	−1.57	0.79	20,578,550
	(0.21)	(0.19)	(0.18)	(0.16)		
Baking	−1.92	−2.41	−2.41	−1.54	0.79	16,709,717
	(0.18)	(0.15)	(0.15)	(0.13)		
Breakfast	−0.69	−1.67	−2.32	−1.69	0.67	16,477,711
	(0.24)	(0.22)	(0.21)	(0.18)		
Beverages	−0.36	−1.38	−1.72	−1.35	0.84	14,881,788
	(0.20)	(0.18)	(0.17)	(0.15)		
Pasta and prep. Food	−0.69	−1.48	−1.98	−1.47	0.79	15,506,753
	(0.23)	(0.20)	(0.19)	(0.17)		
Panel B						
Frozen foods	−0.99	−1.75	−2.14	−1.63	0.82	19,589,916
	(0.24)	(0.20)	(0.19)	(0.17)		
Dairy	−1.62	−2.03	−2.30	−1.68	0.83	23,149,077
	(0.19)	(0.16)	(0.16)	(0.14)		
Deli, pack. meat, fr. prod	−2.67	−3.19	−2.96	−1.90	0.76	20,588,587
	(0.20)	(0.17)	(0.16)	(0.14)		
Panel C						
Alcohol and gen. merch.	−1.86	−1.67	−1.78	−1.12	0.92	12,100,738
	(0.17)	(0.15)	(0.14)	(0.12)		
Non-food grocery	−0.70	−0.93	−1.27	−1.20	0.89	21,070,712
	(0.22)	(0.19)	(0.20)	(0.17)		
Health and beauty aids	−1.28	−1.28	−1.76	−1.47	0.83	17,843,402
	(0.34)	(0.29)	(0.29)	(0.23)		

NOTES: Percentage change in prices for same product as a function of income quintile (top quintile excluded). Percentage change computed as (100*exp(β)-1). *Panel A:* dry groceries by sub-department; *Panel B:* other food items; *Panel C:* non-food items. *Dependent variable:* log pretax unit price (net of coupons) paid on average by a given household for product (identified at barcode level) during quarter-year. *Controls:* age of the head of household, household size, quarter-year, CBSA (ca. 1000 areas) and product fixed effects. All regressions include a constant. Robust standard error clustered at the household level reported in parentheses (ca. 144,000 clusters). Figures are computed using sampling weights provided by Nielsen. *Sample:* Nielsen Consumer Panel dataset, years 2008-2015.

[17] Households that do not reside in CBSAs are not included in the sample of the regressions in Tables A4-A12.

Table A5: PRICE HETEROGENEITY – BRAND-MODULE LEVEL

Product Department	Lowest	Second	Third	Fourth	Adj R^2	Obs.
Panel A						
Candy	0.19	−0.64	−1.51	−1.17	0.69	16,794,270
	(0.26)	(0.22)	(0.21)	(0.19)		
Baking	−4.12	−4.34	−3.95	−2.50	0.79	13,493,570
	(0.23)	(0.20)	(0.19)	(0.17)		
Breakfast	−2.05	−2.79	−3.03	−2.21	0.68	13,434,316
	(0.29)	(0.25)	(0.24)	(0.21)		
Beverages	0.85	−1.03	−1.79	−1.61	0.89	11,112,357
	(0.32)	(0.28)	(0.26)	(0.22)		
Pasta and prep. Food	−3.56	−4.03	−3.88	−2.70	0.72	11,254,170
	(0.26)	(0.24)	(0.22)	(0.20)		
Panel B						
Frozen foods	−3.04	−3.42	−3.39	−2.37	0.73	15,338,331
	(0.26)	(0.22)	(0.21)	(0.19)		
Dairy	−4.01	−3.99	−3.84	−2.66	0.84	16,383,744
	(0.23)	(0.20)	(0.20)	(0.18)		
Deli, pack. meat, fr. prod	−7.32	−6.95	−5.80	−3.59	0.81	17,015,525
	(0.28)	(0.24)	(0.23)	(0.20)		
Panel C						
Alcohol and gen. merch.	−8.62	−6.58	−5.26	−3.05	0.90	10,640,781
	(0.31)	(0.25)	(0.24)	(0.21)		
Non-food grocery	−3.39	−2.58	−2.24	−1.52	0.91	18,435,596
	(0.26)	(0.23)	(0.23)	(0.20)		
Health and beauty aids	−3.98	−3.15	−2.80	−2.11	0.89	16,088,154
	(0.38)	(0.33)	(0.32)	(0.27)		

NOTES: Percentage change in prices for same product as a function of income quintile (top quintile excluded). Percentage change computed as (100*exp(β)-1). *Panel A:* dry groceries by sub-department; *Panel B:* other food items; *Panel C:* non-food items. *Dependent variable:* log pretax unit price (net of coupons) paid on average by a given household for product (identified at brand-module level) during quarter-year. *Controls:* age of the head of household, household size, quarter-year, CBSA and product fixed effects. All regressions include a constant. Robust standard error clustered at the household level reported in parentheses (ca. 144,000 clusters). Figures are computed using sampling weights provided by Nielsen. *Sample:* Nielsen Consumer Panel dataset, years 2008-2015.

Table A6: PRICE HETEROGENEITY – MODULE LEVEL

Product Department	Lowest	Second	Third	Fourth	Adj R^2	Obs.
Panel A						
Candy	−5.53	−5.29	−5.24	−3.39	0.55	9,772,845
	(0.34)	(0.28)	(0.27)	(0.24)		
Baking	−10.44	−9.39	−7.70	−4.65	0.71	9,868,126
	(0.31)	(0.27)	(0.26)	(0.23)		
Breakfast	−13.26	−11.76	−9.49	−6.06	0.52	7,625,029
	0.41	0.33	0.32	0.28		
Beverages	−9.21	−8.77	−7.35	−4.60	0.85	6,376,671
	(0.42)	(0.35)	(0.34)	(0.30)		
Pasta and prep. Food	−11.81	−10.65	−8.71	−5.39	0.53	8,372,464
	(0.35)	(0.31)	(0.29)	(0.26)		
Panel B						
Frozen foods	−13.18	−11.48	−9.37	−5.80	0.54	11,187,363
	(0.35)	(0.30)	(0.29)	(0.26)		
Dairy	−9.19	−8.36	−7.13	−4.61	0.79	12,015,533
	(0.30)	(0.26)	(0.25)	(0.22)		
Deli, pack. meat, fr. prod	−14.13	−12.33	−9.90	−5.91	0.75	12,136,955
	(0.37)	(0.32)	(0.31)	(0.27)		
Panel C						
Alcohol and gen. merch.	−22.66	−18.00	−13.54	−7.96	0.81	8,170,250
	(0.50)	(0.40)	(0.38)	(0.34)		
Non-food grocery	−16.69	−12.77	−9.57	−5.37	0.81	14,979,526
	(0.41)	(0.34)	(0.32)	(0.28)		
Health and beauty aids	−19.74	−15.18	−11.17	−6.71	0.79	13,057,337
	(0.54)	(0.44)	(0.43)	(0.36)		

NOTES: Percentage change in prices for same product as a function of income quintile (top quintile excluded). Percentage change computed as (100*exp(β)-1). *Panel A:* dry groceries by sub-department; *Panel B:* other food items; *Panel C:* non-food items. *Dependent variable:* log pretax unit price (net of coupons) paid on average by a given household for product (identified at module level) during quarter-year. *Controls:* age of the head of household, household size, quarter-year, CBSA and product fixed effects. All regressions include a constant. Robust standard error clustered at the household level reported in parentheses (ca. 144,000 clusters). Figures are computed using sampling weights provided by Nielsen. *Sample:* Nielsen Consumer Panel dataset, years 2008-2015.

Table A7: PRICE HETEROGENEITY – GROUP LEVEL

Product Department	Lowest	Second	Third	Fourth	Adj R^2	Obs.
Panel A						
Candy	−6.89	−6.11	−6.00	−3.93	0.50	3,507,024
	(0.40)	(0.33)	(0.32)	(0.29)		
Baking	−14.17	−12.14	−9.87	−6.00	0.61	4,646,065
	(0.41)	(0.35)	(0.34)	(0.30)		
Breakfast	−16.24	−14.43	−11.48	−7.19	0.28	5,266,645
	(0.48)	(0.39)	(0.38)	(0.34)		
Beverages	−10.38	−9.66	−8.08	−5.02	0.84	3,938,417
	(0.52)	(0.43)	(0.42)	(0.37)		
Pasta and prep. Food	−13.40	−12.22	−10.14	−6.39	0.25	4,819,908
	(0.42)	(0.36)	(0.35)	(0.31)		
Panel B						
Frozen foods	−13.90	−12.11	−9.70	−6.05	0.56	6,274,959
	(0.38)	(0.31)	(0.31)	(0.27)		
Dairy	−14.01	−12.36	−9.88	−6.22	0.73	7,076,219
	(0.37)	(0.30)	(0.30)	(0.27)		
Deli, pack. meat, fr. prod	−20.64	−17.65	−13.94	−8.53	0.70	4,551,692
	(0.47)	(0.39)	(0.38)	(0.33)		
Panel C						
Alcohol and gen. merch.	−25.29	−19.90	−15.32	−9.05	0.73	5,877,616
	(0.60)	(0.49)	(0.47)	(0.41)		
Non-food grocery	−16.17	−12.32	−9.70	−5.41	0.48	8,867,554
	(0.55)	(0.45)	(0.42)	(0.38)		
Health and beauty aids	−24.33	−18.41	−13.65	−8.10	0.53	9,358,679
	(0.65)	(0.52)	(0.51)	(0.43)		

NOTES: Percentage change in prices for same product as a function of income quintile (top quintile excluded). Percentage change computed as (100*exp(β)-1). *Panel A:* dry groceries by sub-department; *Panel B:* other food items; *Panel C:* non-food items. *Dependent variable:* log pretax unit price (net of coupons) paid on average by a given household for product (identified at group level) during quarter-year. *Controls:* age of the head of household, household size, quarter-year, CBSA and product fixed effects. All regressions include a constant. Robust standard error clustered at the household level reported in parentheses (ca. 144,000 clusters). Figures are computed using sampling weights provided by Nielsen. *Sample:* Nielsen Consumer Panel dataset, years 2008-2015.

A.3.2 Price regressions across years

Tables A8-A11 find that price heterogeneity decreased over time.

Table A8: PRICE HETEROGENEITY – UPC LEVEL

Year	Lowest	Second	Third	Fourth	Adj R^2	Obs.
2008	−2.12	−2.65	−2.50	−1.73	0.88	30,644,388
	(0.29)	(0.26)	(0.23)	(0.21)		
2009	−1.54	−2.10	−2.33	−1.38	0.87	29,300,281
	(0.30)	(0.27)	(0.25)	(0.23)		
2010	−1.10	−1.76	−2.01	−1.52	0.87	28,796,424
	(0.34)	(0.28)	(0.28)	(0.25)		
2011	−0.76	−1.47	−2.17	−1.79	0.86	29,522,302
	(0.34)	(0.28)	(0.30)	(0.27)		
2012	−1.37	−1.76	−2.20	−1.75	0.86	27,676,511
	(0.31)	(0.27)	(0.27)	(0.25)		
2013	−0.77	−1.37	−1.60	−1.42	0.86	26,813,535
	(0.30)	(0.26)	(0.29)	(0.23)		
2014	−0.37	−1.11	−1.07	−1.00	0.88	26,886,833
	(0.24)	(0.22)	(0.23)	(0.20)		
2015	−0.60	−1.06	−1.25	−0.87	0.89	25,866,925
	(0.22)	(0.20)	(0.19)	(0.17)		

NOTES: Percentage change in prices for same product as a function of income quintile (top quintile excluded). Percentage change computed as (100*exp(β)-1). *Dependent variable:* log pre-tax unit price (net of coupons) paid on average by a given household for product (identified at barcode level) during quarter-year. *Controls:* age of the head of household, household size, quarter-year, CBSA (ca. 1000 areas) and product fixed effects. All regressions include a constant. Robust standard error clustered at the household level reported in parentheses (ca. 144,000 clusters). Figures are computed using sampling weights provided by Nielsen. *Sample:* Nielsen Consumer Panel dataset, years 2008-2015.

Table A9: PRICE HETEROGENEITY – BRAND-MODULE LEVEL

Year	Lowest	Second	Third	Fourth	Adj R^2	Obs.
2008	−4.74	−4.56	−3.91	−2.52	0.90	24,767,815
	(0.35)	(0.31)	(0.29)	(0.27)		
2009	−3.80	−4.04	−3.73	−2.25	0.89	23,713,866
	(0.37)	(0.32)	(0.30)	(0.28)		
2010	−3.36	−3.53	−3.37	−2.39	0.90	23,355,112
	(0.40)	(0.34)	(0.32)	(0.30)		
2011	−3.22	−3.55	−3.75	−2.78	0.89	23,890,726
	(0.41)	(0.33)	(0.35)	(0.32)		
2012	−4.16	−3.76	−3.91	−2.80	0.89	22,451,466
	(0.38)	(0.32)	(0.32)	(0.29)		
2013	−2.98	−3.15	−2.86	−2.14	0.89	21,744,131
	(0.37)	(0.31)	(0.33)	(0.28)		
2014	−2.82	−3.00	−2.44	−1.85	0.89	21,822,322
	(0.31)	(0.27)	(0.28)	(0.25)		
2015	−2.95	−3.06	−2.71	−1.74	0.90	21,036,538
	(0.29)	(0.25)	(0.25)	(0.22)		

NOTES: Percentage change in prices for same product as a function of income quintile (top quintile excluded). Percentage change computed as (100*exp(β)-1). *Dependent variable:* log pre-tax unit price (net of coupons) paid on average by a given household for product (identified at brand-module level) during quarter-year. *Controls:* age of the head of household, household size, quarter-year, CBSA (ca. 1000 areas) and product fixed effects. All regressions include a constant. Robust standard error clustered at the household level reported in parentheses (ca. 144,000 clusters). Figures are computed using sampling weights provided by Nielsen. *Sample:* Nielsen Consumer Panel dataset, years 2008-2015.

Table A10: PRICE HETEROGENEITY – MODULE LEVEL

Year	Lowest	Second	Third	Fourth	Adj R^2	Obs.
2008	−16.03	−13.12	−9.96	−5.96	0.82	17,791,358
	(0.52)	(0.43)	(0.41)	(0.38)		
2009	−13.58	−12.04	−9.38	−5.47	0.82	17,089,326
	(0.53)	(0.44)	(0.42)	(0.38)		
2010	−13.04	−11.09	−8.88	−5.41	0.82	16,838,448
	(0.53)	(0.44)	(0.42)	(0.39)		
2011	−12.89	−11.32	−9.42	−5.85	0.82	17,103,533
	(0.56)	(0.45)	(0.46)	(0.41)		
2012	−14.43	−11.67	−9.83	−6.16	(0.81	16,084,610
	(0.51)	(0.44)	(0.43)	(0.39)		
2013	−13.22	−11.50	−9.09	−5.58	0.81	15,630,340
	(0.51)	(0.42)	(0.43)	(0.38)		
2014	−13.75	−11.57	−8.94	−5.70	0.81	15,684,489
	(0.46)	(0.38)	(0.39)	(0.34)		
2015	−13.80	−11.57	−9.01	−5.42	0.81	15,211,753
	(0.45)	(0.37)	(0.37)	(0.32)		

NOTES: Percentage change in prices for same product as a function of income quintile (top quintile excluded). Percentage change computed as (100*exp(β)-1). *Dependent variable:* log pre-tax unit price (net of coupons) paid on average by a given household for product (identified at module level) during quarter-year. *Controls:* age of the head of household, household size, quarter-year, CBSA (ca. 1000 areas) and product fixed effects. All regressions include a constant. Robust standard error clustered at the household level reported in parentheses (ca. 144,000 clusters). Figures are computed using sampling weights provided by Nielsen. *Sample:* Nielsen Consumer Panel dataset, years 2008-2015.

Table A11: PRICE HETEROGENEITY – GROUP LEVEL

Year	Lowest	Second	Third	Fourth	Adj R^2	Obs.
2008	−19.11	−15.57	−11.65	−6.82	0.71	9,720,093
	(0.59)	(0.48)	(0.45)	(0.42)		
2009	−16.24	−14.34	−10.95	−6.40	0.71	9,360,620
	(0.60)	(0.48)	(0.46)	(0.42)		
2010	−16.20	−13.40	−10.77	−6.57	0.70	9,323,476
	0.59)	(0.49)	(0.47)	(0.43		
2011	−16.18	−13.78	−11.43	−7.09	0.70	9,420,697
	(0.63)	(0.51)	(0.52)	(0.46)		
2012	−17.82	−14.38	−11.87	−7.55	0.69	8,888,898
	(0.57)	(0.49)	(0.48)	(0.43)		
2013	−16.76	−14.20	−11.22	−7.02	0.69	8,690,053
	(0.57)	(0.48)	(0.49)	(0.43)		
2014	−17.45	−14.52	−11.32	−7.20	0.69	8,719,832
	(0.53)	(0.44)	(0.45)	(0.39)		
2015	−17.59	−14.64	−11.22	−6.70	0.68	8,500,351
	(0.52)	(0.43)	(0.42)	(0.37)		

NOTES: Percentage change in prices for same product as a function of income quintile (top quintile excluded). Percentage change computed as (100*exp(β)-1). *Dependent variable:* log pre-tax unit price (net of coupons) paid on average by a given household for product (identified at group level) during quarter-year. *Controls:* age of the head of household, household size, quarter-year, CBSA (ca. 1000 areas) and product fixed effects. All regressions include a constant. Robust standard error clustered at the household level reported in parentheses (ca. 144,000 clusters). Figures are computed using sampling weights provided by Nielsen. *Sample:* Nielsen Consumer Panel dataset, years 2008-2015.

A.3.3 Weighted price regressions

In this section, we run the regression in Table 1 using frequency and expenditure weights. The frequency weights are computed using the frequency of shopping trips within a quarter-year, whereas the expenditure weights are computed using the total expenditure of a household within a quarter-year. Table A12 shows the the results are robust to these two weighting schemes.

Table A12: PRICE HETEROGENEITY - WEIGHTED

Year	Lowest	Second	Third	Fourth	Adj R^2	Obs.
Frequency						
UPC	−1.32	−1.79	−2.07	−1.55	0.87	226,458,924
	(0.18)	(0.16)	(0.16)	(0.14)		
Brand-Module	−3.85	−3.84	−3.65	−2.47	0.90	182,925,772
	(0.23)	(0.20)	(0.20)	(0.17)		
Module	−13.47	−11.49	−9.41	−5.78	0.84	131,434,040
	(0.34)	(0.29)	(0.28)	(0.24)		
Group	−15.44	−13.21	−10.93	−6.77	0.75	72,624,040
	(0.37)	(0.31)	(0.30)	(0.26)		
Expenditure						
UPC	−0.73	−1.15	−1.37	−1.08	0.95	226458924
	(0.13)	(0.11)	(0.11)	(0.09)		
Brand-Module	−2.79	−2.66	−2.53	−1.77	0.94	182,925,772
	(0.20)	(0.16)	(0.16)	(0.14)		
Module	−13.85	−11.57	−9.22	−5.89	0.89	131,434,040
	(0.32)	(0.27)	(0.26)	(0.23)		
Group	−16.07	−13.43	−10.87	−7.05	0.81	72,624,040
	(0.39)	(0.32)	(0.31)	(0.28)		

NOTES: Percentage change in prices for same product as a function of income quintile (top quintile excluded). Percentage change computed as (100*exp(β)-1). *Dependent variable:* log pre-tax unit price (net of coupons) paid on average by a given household for product (identified at different levels) during quarter-year. *Controls:* age of the head of household, household size, quarter-year, CBSA (ca. 1000 areas) and product fixed effects. All regressions include a constant. Robust standard error clustered at the household level reported in parentheses (ca. 144,000 clusters). Figures are computed using sampling weights provided by Nielsen. *Sample:* Nielsen Consumer Panel dataset, years 2008-2015.

A.4 Inequality adjustment

Table A13 reports the actual inequality and the ratios of (5) to (4) for all years. Even years between 2008 and 2015 are depicted in Figure 1.

Table A13: CONSUMPTION INEQUALITY

Year	Consumption inequality	Adjusted inequality (%) UPC	BM	Module	Group
2008	1,080.79	99.24	98.37	97.54	97.41
		(0.16)	(0.25)	(0.50)	(0.55)
2009	1,114.38	98.96	97.83	96.48	96.35
		(0.15)	(0.24)	(0.50)	(0.56)
2010	1,141.10	98.49	97.59	96.37	97.88
		(0.20)	(0.31)	(0.47)	(0.94)
2011	1,204.22	98.54	97.23	96.25	97.84
		(0.19)	(0.32)	(0.50)	(0.80)
2012	1,677.59	98.58	97.61	96.38	99.12
		(0.18)	(0.35)	(0.58)	(0.83)
2013	1,716.53	98.88	97.66	97.38	99.75
		(0.24)	(0.35)	(0.78)	(1.42)
2014	1,768.63	99.15	98.15	98.03	99.51
		(0.19)	(0.29)	(0.54)	(0.70)
2015	1,680.28	99.21	98.55	99.14	102.12
		(0.22)	(0.33)	(0.55)	(0.98)

NOTES: Inequality computed as standard deviation of consumption expenditures, with products defined at brand-module levels. Figures are computed using sampling weights provided by Nielsen and adjusted using the adult-equivalence scale. Columns third to sixth report adjusted consumption inequality (average prices) as a percentage of actual consumption inequality, at different product definitions. Non-parametric bootstrap standard errors reported in parenthesis (500 replications).

A.4.1 Alternative inequality measures

Table A14: PRODUCT DEFINITION: UPC

Year	Std. dev.	IQR	Ratios 90-10	90-50	50-10
2008	99.24	99.64	99.35	99.39	99.96
2009	98.96	100.57	100.53	99.96	100.57
2010	98.49	100.27	99.61	99.68	99.93
2011	98.54	99.38	99.32	99.10	100.23
2012	98.58	99.42	99.22	99.46	99.76
2013	98.88	100.00	99.63	99.39	100.24
2014	99.15	98.76	99.91	100.15	99.76
2015	99.21	100.79	100.23	99.78	100.46

NOTES: Measures of inequality computed at UPC level. Figures are computed using sampling weights provided by Nielsen and adjusted using the adult-equivalence scale. Columns second to sixth report adjusted consumption inequality (average prices) as a percentage of actual consumption inequality, at UPC product definition. The second column reports, for reference, the same figures shown in Table A13 and Figure 1.

Table A15: PRODUCT DEFINITION: BRAND-MODULE

Year	Std. dev.	IQR	Ratios		
			90-10	90-50	50-10
2008	98.37	98.78	98.18	98.67	99.51
2009	97.83	99.16	99.91	99.12	100.80
2010	97.59	99.72	98.57	98.89	99.67
2011	97.23	98.92	98.42	98.18	100.25
2012	97.61	98.54	98.25	97.87	100.39
2013	97.66	98.66	99.33	98.97	100.36
2014	98.15	99.33	98.73	98.50	100.22
2015	98.55	101.11	99.62	99.45	100.17

NOTES: Measures of inequality computed at brand-module level. Figures are computed using sampling weights provided by Nielsen and adjusted using the adult-equivalence scale. Columns second to sixth report adjusted consumption inequality (average prices) as a percentage of actual consumption inequality, at brand-module product definition. The second column reports, for reference, the same figures shown in Table A13 and Figure 1.

Table A16: PRODUCT DEFINITION: MODULE

Year	Std. dev.	IQR	Ratios		
			90-10	90-50	50-10
2008	97.54	97.08	97.43	97.69	99.73
2009	96.48	97.46	97.41	97.54	99.87
2010	96.37	97.52	97.32	98.36	98.94
2011	96.25	98.69	97.78	97.64	100.14
2012	96.38	97.99	97.15	97.25	99.91
2013	97.38	98.48	98.29	97.56	100.75
2014	98.03	98.56	98.79	98.59	100.21
2015	99.14	100.13	100.68	99.10	101.59

NOTES: Measures of inequality computed at module level. Figures are computed using sampling weights provided by Nielsen and adjusted using the adult-equivalence scale. Columns second to sixth report adjusted consumption inequality (average prices) as a percentage of actual consumption inequality, at module product definition. The second column reports, for reference, the same figures shown in Table A13 and Figure 1.

Table A17: PRODUCT DEFINITION: GROUP

Year	Std. dev.	IQR	Ratios		
			90-10	90-50	50-10
2008	97.41	97.23	97.89	97.79	100.10
2009	96.35	97.60	97.77	97.01	100.79
2010	97.88	98.74	98.40	98.60	99.80
2011	97.84	99.12	98.10	97.10	101.03
2012	99.12	97.83	98.48	97.28	101.24
2013	99.75	98.96	100.43	98.31	102.16
2014	99.51	98.43	99.94	98.54	101.42
2015	102.12	100.60	102.78	98.93	103.89

NOTES: Measures of inequality computed at group level. Figures are computed using sampling weights provided by Nielsen and adjusted using the adult-equivalence scale. Columns second to sixth report adjusted consumption inequality (average prices) as a percentage of actual consumption inequality, at group product definition. The second column reports, for reference, the same figures shown in Table A13 and Figure 1.

A.5 Evidence on basket composition

Table A18 shows suggestive evidence in support of the relationship between household income and the composition of the consumption basket. Table A18 reports the average number of distinct barcode-level products purchased by households by income quintiles, and shows that rich households purchase on average about 20 percent more distinct products than poor households. We interpret this empirical fact as evidence of a composition factor behind consumption inequality.

Table A18: AVERAGE NUMBER OF UPCS BY INCOME

Year	Lowest	Second	Third	Fourth	Top
2008	480	546	590	617	594
2009	469	532	577	601	594
2010	462	533	567	592	578
2011	477	543	586	608	595
2012	473	539	575	597	586
2013	462	529	559	579	568
2014	472	529	553	575	555
2015	460	513	539	554	537

NOTES: Average number of products (identified at barcode level) purchased by households in each income quintile across all departments. *Sample:* Nielsen Consumer Panel dataset.