Price Heterogeneity and Consumption Inequality

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Abstract

Using the Nielsen Consumer Panel, we document the presence of significant price heterogeneity in the United States. Poor households pay lower prices for the same products, mostly because they shop more at discount stores. However, we also find that price heterogeneity has a very small impact on the measurement of consumption inequality. Adjusting nominal household expenditures by imposing that all products have the same price does not appreciably reduce consumption inequality in the United States. Finally, we decompose our inequality measure into two factors, measuring differences in the composition and size of consumption baskets. Variations in composition and quantity are both very important in explaining consumption inequality, and the two factors appear to be highly correlated.

Keywords: Consumption Inequality, Price Heterogeneity, Nielsen Panel

JEL Codes: E32, D20, C30

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1 Introduction

We document that households systematically pay different prices for the same exact products, and this price heterogeneity is correlated with income: lower income households pay on average lower prices than higher income ones. Such heterogeneity might have a considerable impact on the measurement of consumption inequality; in other words, if poor households systematically pay lower prices than their richest counterparts, existing measures of consumption inequality may be biased upwards. We provide empirical evidence that price heterogeneity does not matter for the measurement of consumption inequality.

The recent academic literature has shown considerable interest in the measurement of the level and trend of the 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 et al. (2008) show that wage inequality has risen substantially in recent decades. More controversial is the claim that consumption inequality had a similar trend. Recent work by Attanasio and Pistaferri (2014), Attanasio et al. (2012) and Aguiar and Bils (2015) suggests that consumption inequality, as measured by expenditure inequality, has increased over time in the same way as income inequality, once measurement error issues are taken care of.

Consumption is usually measured using surveys on household expenditures. Aguiar and Hurst (2005) were the first to show that there are significant differences between expenditure and consumption by households, as the time invested in the search for lower prices crucially depends on the age, income and education composition of the household. Broda and Romalis (2009) show that over 1994-2005 low-income households experienced a much lower price inflation than high-income households, therefore lowering the slope of the increasing trend in real income inequality over the same period. In a similar vein, Moretti (2013) shows that skilled workers since 1980 disproportionately concentrated in cities with increasingly higher costs of living and therefore experienced higher price inflation than unskilled workers, suggesting that real wage inequality grew less than in nominal terms.

We provide evidence on the importance of price heterogeneity in the measurement of consumption inequality. Using the Nielsen Consumer Panel Data, we first document significant price heterogeneity in the United States.[1] A household in the bottom income quintile on average pays $5 - 10\%$ less than a household in the top quintile for the same exact products,

[1] The results in this paper were calculated (or derived) based on data from The Nielsen Company (US), LLC and marketing databases provided by the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business.

and up to 20% less if we define products into coarser categories. We show that the price differential, at the barcode level, is due to a different intensity in the search for lower prices. However, the higher price differential computed at wider product definitions is in part due to quality differences. Poor households tend to buy products of lower quality and hence of lower prices than rich households. The evidence we uncover suggests that researchers need to be careful when estimating price differentials, as aggregation of similar products might hide significant quality differences.

Our findings are consistent with previous research on diverging inflation rates for lower and higher income households in the past few decades. As suggested by previous research, consumption inequality might be influenced by these systematic differences in prices. We adjust expenditure inequality by imposing that the same products have the same prices, using barcode-level as well as broader definitions of products. In all cases, consumption inequality decreases very little when we impose homogeneous prices. This evidence shows that consumption inequality depends mostly on the quantity and quality of what is consumed and not on its price.

Finally, we explore the roles of "composition heterogeneity" and "quantity heterogeneity". If correcting for price heterogeneity does not have a significant impact, it must be that most of the inequality is due to either households consuming different products, "composition heterogeneity", or households consuming different quantities of the same products, "quantity heterogeneity". We find that both types of heterogeneity play an important role.

The Nielsen Consumer Panel covers only grocery expenditures. Broda and Parker (2014) report that spending per capita in the Nielsen Consumer Panel is about 10% of the NIPA per capita PCE and, household spending is around 35% of spending on nondurable goods in the Consumption Expenditure Survey. Moreover, they report that the Nielsen Consumer Panel covers around 40% of all expenditure on goods in the CPI. All told, these numbers suggest that Nielsen data is not a good source to measure overall consumption inequality. However, price heterogeneity is most prominent in grocery spending, where price discrimination significantly increased over the past two decades. For this reason, we think that the Nielsen Consumer Panel offers an excellent setting where to study the impact of price heterogeneity on the measurement of inequality.

The rest of the paper is organized as follows. Section 2 introduces the data we use in the paper and provides a comparison with another frequently used dataset on consumption, the Consumption Survey Expenditure. Section 3 provides evidence on price heterogeneity in the United States. Section 4 explains how we measure inequality and how we decompose it into its determinants. Sections 5 and 6 present the empirical results, and Section 7 concludes.

2 Data description

The Nielsen Consumer Panel follows from 40,000 to 60,000 households, depending on the survey year, in their day-to-day grocery purchases.[2] Each panelist is provided with a in-home scanner to record all the purchases of all Nielsen-tracked products from many outlets in the United States. Nielsen tries 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. The dataset goes from 2004 to 2014. Each entry in the dataset represents the purchase of a barcode-level product and is associated with information on both the product and the outlet: price, quantity purchased, product characteristics, retailer type, location, etc. The dataset also provides demographic information on the households participating in the panel. Following the literature, we drop households whose head is younger than 25 or older than 65 years old. We also drop households with size equal or higher than 9, as we do not observe the precise size of those households.

In our analysis the main variables of interest will be the quantity purchased and the price paid for each product. Prices are collected in two different ways. When the panelist inputs a purchase in the scanner, if the store provides point of sale data to Nielsen, the price of the product is imputed by Nielsen as the average weighted price for the item that week in that particular store. If the store where the product was purchased does not provide point of sale data to Nielsen, the panelist is instructed to enter the price paid, prior to any coupons or deals. The panelist is then asked whether he received a discount and has to input the discount in the scanner. Following the previous literature, we compute the price as the difference between the purchase price and the discount.

Using the Nielsen panel, there are two ways to compute annual consumption. For each trip to a store, the panelist has to first input the total amount spent on the trip, and then separately input the expenditure on each product purchased. It has been noted by Einav et al. (2010) 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 omit to report the purchase of some products. In the main analysis, we will work with the

[2]The data was collected by the Nielsen Company (US), LLC. The data is made available through the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. Information on availability and access to the data can be found at http://research.chicagobooth.edu/nielsen/

expenditures on single products and we will therefore have to compute annual consumption summing up those expenditures.

In Table 1, we show mean annual consumption measured in both ways with Nielsen data and measured with CEX data. The weighted averages are computed with the demographic weights provided by Nielsen and CEX and transformed in adult-equivalent terms using the OECD scale.[3] As noted before, household consumption computed summing up all expenditures is lower than when computed using the total amounts spent on each trip. Our preferred measure of consumption in Nielsen seems to be on average about three quarters of consumption as measured in CEX.

Table 1: Mean consumption in CEX and Nielsen in $

Dates	CEX	Nielsen	
	Grocery exp.	Total exp.	Total spent
2004	2,528	1,737	2,820
2005	2,631	1,761	2,833
2006	2,753	1,816	2,897
2007	2,824	1,852	3,171
2008	3,032	1,900	3,265
2009	2,954	1,921	3,211
2010	2,967	1,926	3,348
2011	3,090	2,010	3,496
2012	3,201	2,473	3,466
2013	3,258	2,480	3,402
2014	3,305	2,567	3,498

Source: CEX, Nielsen and own calculations.

The first column of Table 2 reports for each year the mean ratios of our preferred measure of consumption to the one computed using the total amount spent on each trip. The reporting rate is around 60% for every year before 2012, when it jumps to 70%. This jump in the reporting rate fully explains the sharp increase in our preferred measure of annual expenditure since 2012. As it will be clear later, the main results of the paper go through if we exclude the data from 2012 from the analysis.

Since the reporting rate is lower than 100%, it is important to investigate whether it is in any way related to the income of the households, which might bias the measurement of

[3]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 kids in the household, where a kid is defined as younger than 18 years old.

Table 2: Household reporting rate

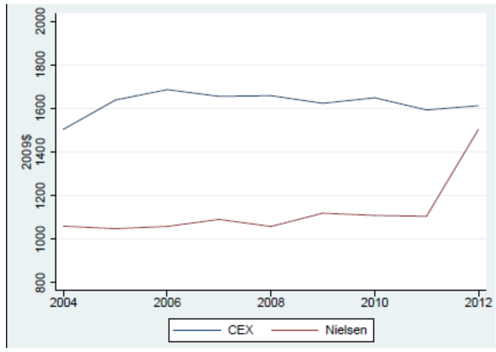
	Mean	Regression					
		Lowest	Second	Third	Fourth	Adj R^2	Obs.
2004	62.6	3.62	2.17	1.23	0.92	0.01	28,679
		(0.40)	(0.33)	(0.33)	(0.30)		
2005	63.1	3.71	2.37	1.89	1.45	0.01	27,894
		(0.43)	(0.35)	(0.36)	(0.34)		
2006	63.6	3.16	2.12	1.81	1.27	0.01	26,862
		(0.49)	(0.39)	(0.38)	(0.35)		
2007	60.6	3.37	1.67	1.10	0.31	0.01	48,842
		(0.36)	(0.29)	(0.28)	(0.26)		
2008	60.6	3.20	1.61	1.15	0.85	0.01	46,524
		(0.40)	(0.32)	(0.31)	(0.29)		
2009	61.9	3.25	1.49	1.31	1.16	0.01	45,191
		(0.38)	(0.31)	(0.31)	(0.28)		
2010	60.4	3.90	2.06	1.21	0.97	0.01	45,170
		(0.39)	(0.32)	(0.31)	(0.29)		
2011	60.7	4.10	2.18	1.86	0.78	0.01	45,648
		(0.41)	(0.35)	(0.35)	(0.32)		
2012	71.7	3.60	2.98	2.37	1.65	0.01	43,643
		(0.34)	(0.28)	(0.28)	(0.27)		
2013	73.5	3.46	3.37	2.73	1.71	0.01	43,434
		(0.32)	(0.27)	(0.28)	(0.26)		
2014	74.2	3.58	3.27	2.80	1.75	0.01	43,716
		(0.29)	(0.24)	(0.25)	(0.23)		

NOTES: We measure the reporting rate as the ratio of the total expenditure to total spent. In the first column, we report the unconditional means. The regressions include the ratio as dependent variable and income quintile dummies as controls plus a constant. The top quintile dummy is omitted. Standard errors are in parentheses.

consumption inequality. For this reason, we report in Table 2 some simple regressions of the reporting rate on income quintile dummies. Lower income household 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 2 demonstrate that the income level of the household does not statistically explain much of the variation in the reporting ratios.

Figure 1 shows the evolution of consumption inequality in the CEX and in Nielsen. Inequality is measured as the standard deviation of annual household consumption adjusted with the adult equivalence scale and deflated with the nondurable goods component of the PCE deflator. Inequality measured with CEX data is a touch higher, consistently with averages being higher, as shown in Table 1; however, the two measures are both similarly flat.

Figure 1: Consumption Inequality in CEX and Nielsen



The jump in 2012 in consumption inequality as measured with Nielsen is due to the jump in the reporting ratio in the same year, as explained earlier.

Table 3: Frequency of shopping

	Obs.	Share in %
5+ times/week	321	0.25
3-5 times/week	8,627	6.81
1-2 times/week	85,506	67.52
> Once/month	31,905	25.19
< One/month	281	0.22

Source: Nielsen and own calculations.

Table 3 shows the frequency of shopping for the households in our dataset. Almost all households shop at least once a month and most of them shop once or twice per week. Finally, Tables 4 and 5 present some demographic information on the households from the 2010 survey. Table 4 shows that the unweighted Nielsen panel is not representative of the U.S. population along the household income dimension. For this reason, we will use the demographic weights provided by Nielsen to make the sample more representative. It must be noted that even using the demographic weights, the Nielsen data somewhat under-represents the lowest income quintile. Table 5 provides unweighted statistics on household composition and the education of the head of the household from the 2010 survey.

Table 4: Household income 2010

	Obs.	Nielsen Share in %		Census Share in %
		Unweighted	Weighted	
$\$0 - \$19,000$	3,970	8.8	12.9	20
$\$20,000 - \$39,999$	9,399	20.8	21.2	20
$\$40,000 - \$59,999$	10,326	22.9	19.6	20
$\$60,000 - \$99,999$	14,007	31.0	24.3	20
$> \$100,000$	7,469	16.5	22.1	20

Source: Nielsen and own calculations.

Table 5: Demographic Statistics - 2010

HH composition	Obs.	Share in %	Head education	Obs.	Share in %
Married with children	10,773	23.9	Grade School	202	0.45
Single with children	721	1.6	Some High School	1,321	2.92
Married, no children	17,358	38.4	Graduated High School	10,341	22.89
Single, no children	7, 414	16.4	Some College	13,308	29.46
Other	8,904	19.7	Graduated College	14,248	31.54
			Graduate School	5,750	12.73

Source: Nielsen and own calculations. Unweighted statistics.

3 Price heterogeneity

Several papers in the literature, such as Handbury and Weinstein (2015) and Kaplan and Menzio (2015), show that there is significant price heterogeneity in the United States. We are especially interested here in showing that low-income households pay lower prices for the same products, which was first documented using Nielsen data by Broda et al. (2009). We will use four different levels of product definition: the barcode level, which includes about two million products; the brand-module level, BM from here onwards, which aggregates barcode-level products to around 260,000 units, the module level, which aggregates barcode-level products to about 1,500 modules; and finally the group level, which aggregates barcode-level products to around two hundred groups. We create these product definitions relying on

Nielsen's product categories and some product characteristics like unit size and brand.[4]

Table 6: Price heterogeneity - UPC level

	Lowest	Second	Third	Fourth	Adj R^2	Obs.
Health and beauty aids	-0.10	-0.07	-0.05	-0.03	0.67	25,722,182
	(0.00)	(0.00)	(0.00)	(0.00)		
Candy	-0.06	-0.05	-0.04	-0.03	0.73	28,923,037
	(0.00)	(0.00)	(0.00)	(0.00)		
Baking	-0.06	-0.05	-0.04	-0.03	0.74	24,282,697
	(0.00)	(0.00)	(0.00)	(0.00)		
Breakfast	-0.04	-0.04	-0.04	-0.03	0.63	22,956,114
	(0.00)	(0.00)	(0.00)	(0.00)		
Beverages	-0.03	-0.03	-0.03	-0.02	0.80	21,208,273
	(0.00)	(0.00)	(0.00)	(0.00)		
Pasta and prep. food	-0.04	-0.04	-0.04	-0.02	0.75	22,036,605
	(0.00)	(0.00)	(0.00)	(0.00)		
Frozen foods	-0.04	-0.04	-0.04	-0.02	0.74	28,836,449
	(0.00)	(0.00)	(0.00)	(0.00)		
Dairy	-0.04	-0.04	-0.04	-0.02	0.75	31,840,906
	(0.00)	(0.00)	(0.00)	(0.00)		
Deli, pack. meat, fresh prod.	-0.06	-0.05	-0.04	-0.03	0.68	30,808,800
	(0.00)	(0.00)	(0.00)	(0.00)		
Non-food grocery	-0.06	-0.05	-0.04	-0.03	0.77	30,877,252
	(0.00)	(0.00)	(0.00)	(0.00)		
Alcohol, and gen. merch.	-0.15	-0.11	-0.08	-0.05	0.71	18,322,485
	(0.00)	(0.00)	(0.00)	(0.00)		

NOTES: The dependent variable is the natural logarithm of the average price paid. Controls include, product fixed effects, region fixed effects, quarterly time fixed effects, the age of the head of household, a dummy equal to one if the head of household is African American, a dummy equal to 1 if the head of household is Hispanic, and finally household size. Standard errors are in parentheses.

The barcode-level is the most detailed product definition and it perfectly identifies the products that are sold by a supermarket. However, the same type of product, for instance a specific brand of soda, will be sold in different packaging options, (single 8-ounces can, 6-pack, 12-pack, half-gallon bottle, etc.), and each will have a different UPC number. The BM product definition was introduced by Handbury and Weinstein (2015) to identify products independently of the packaging. The module and group levels, instead, provide wider product definition which aggregate different brands. For instance, cracker is a group that is divided into 5 modules: flaked soda, flavored snack, graham, oyster and remaining. Within modules

[4]For instance, we divide some Nielsen modules that contain products with different unit sizes to make it possible for us to compare their prices.

and groups, there might be significant quality differences.

Table 7: Price heterogeneity - BM level

	Lowest	Second	Third	Fourth	Adj R^2	Obs.
Health and beauty aids	-0.15	-0.11	-0.07	-0.04	0.67	23,113,703
	(0.00)	(0.00)	(0.00)	(0.00)		
Dry grocery	-0.10	-0.09	-0.07	-0.05	0.66	125,978,898
	(0.00)	(0.00)	(0.00)	(0.00)		
Frozen foods	-0.10	-0.09	-0.08	-0.05	0.70	21,893,570
	(0.00)	(0.00)	(0.00)	(0.00)		
Dairy	-0.09	-0.08	-0.07	-0.05	0.77	22,579,794
	(0.00)	(0.00)	(0.00)	(0.00)		
Deli, pack. meat, fresh prod.	-0.13	-0.11	-0.09	-0.05	0.77	23,686,334
	(0.00)	(0.00)	(0.00)	(0.00)		
Non-food grocery	-0.08	-0.06	-0.05	-0.03	0.75	26,964,177
	(0.00)	(0.00)	(0.00)	(0.00)		
Alcohol, and gen. merch.	-0.07	-0.04	-0.02	-0.01	0.72	15,975,832
	(0.00)	(0.00)	(0.00)	(0.00)		

NOTES: Same as Table 6.

We provide evidence on price heterogeneity by running regressions of the average log price paid by a household in a quarter for a product on income quintile dummies, product, region and time fixed effects and demographic controls, age and race of the head of the household and household size; the top income quintile is omitted. We run the regression at each of the four product level definitions. There are too many observations to run regressions with product fixed effects at all product levels except for the group level. For this reason, we decompose product definitions into sub-categories, which roughly correspond to the departments defined by Nielsen, and run regressions with product fixed effects within these sub-categories.[5]

Table 6 presents the results of the regressions at the UPC level, Table 7 at the BM level, Table 8 at the module level, and finally Table 9 at the group level. The results suggest that poor households pay lower prices for the same products at every level of product definition. At the barcode level, lower income households pay on average 5% less than higher income households; this result is broadly consistent with Broda et al. (2009) which ran similar

[5]The Nielsen departments are: health and beauty aids, dry grocery, frozen foods, dairy, deli, packaged meat, fresh produce, non-food grocery, alcohol, and general merchandise. We merged deli, packaged meat, and fresh produce into one department and alcohol, and general merchandise into another department. Only for the barcode-level, we had to break the dry grocery department in 5 sub-categories, candy, baking, breakfast, beverages, and pasta and prepared food.

regressions using only food items in the 2005 Nielsen panel. At the BM level, which is our preferred product definition, poor households pay on average 10% less than the rich. More generally, the wider is the product definition the higher is the price differential. At the group level, the poor pay 20% less. The price differential at the barcode and BM levels are the most relevant, as quality differences can explain price gaps at the module or group levels.

Table 8: Price heterogeneity - Module level

	Lowest	Second	Third	Fourth	Adj R^2	Obs.
Health and beauty aids	-0.29	-0.21	-0.14	-0.08	0.36	18,700,371
	(0.00)	(0.00)	(0.00)	(0.00)		
Dry grocery	-0.19	-0.16	-0.12	-0.07	0.38	84,612,102
	(0.00)	(0.00)	(0.00)	(0.00)		
Frozen foods	-0.18	-0.15	-0.12	-0.07	0.61	16,102,401
	(0.00)	(0.00)	(0.00)	(0.00)		
Dairy	-0.16	-0.14	-0.11	-0.07	0.60	16,543,896
	(0.00)	(0.00)	(0.00)	(0.00)		
Deli, pack. meat, fresh prod.	-0.22	-0.18	-0.14	-0.08	0.49	17,323,656
	(0.00)	(0.00)	(0.00)	(0.00)		
Non-food grocery	-0.15	-0.12	-0.09	-0.05	0.46	21,794,578
	(0.00)	(0.00)	(0.00)	(0.00)		
Alcohol, and gen. merch.	-0.20	-0.15	-0.11	-0.06	0.53	12,315,030
	(0.00)	(0.00)	(0.00)	(0.00)		

NOTES: Same as Table 6.

Table 9: Price heterogeneity - Group level

	Lowest	Second	Third	Fourth	Adj R^2	Obs.
All products	-0.21	-0.17	-0.13	-0.07	0.33	103,015,589
	(0.00)	(0.00)	(0.00)	(0.00)		

NOTES: Same as Table 6.

In Table 10, we investigate the reasons for the price differentials found in Tables 6-9. We first compute for each family in the dataset the fraction of the expenditure associated with the use of a deal, a coupon, a purchase done at a discount store or a purchase of a large size item.[6] We then regress these fractions on income dummies and other controls. We find that

[6] We follow Nevo and Wong (2015) and define large size item the UPC products that rank in the top 40% of the size distribution within each module. We use Nielsen's categorization of stores to identify discount stores.

there is not much difference between rich and poor households in the use of deals, coupons, and large size items. However, poor households spend about 8% more than rich households in discount stores, which might be responsible for most the price differentials we find, especially at the barcode and BM levels.

Table 10: Fraction of expenditure

	Deal	Coupons	Discount stores	Large items
Lowest	-0.03	-0.02	0.08	-0.02
	(0.00)	(0.00)	(0.00)	(0.00)
Second	-0.02	-0.01	0.09	-0.01
	(0.00)	(0.00)	(0.00)	(0.00)
Third	-0.01	-0.01	0.07	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Fourth	-0.00	-0.00	0.04	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Adj R^2	0.04	0.03	0.11	0.06
Region FE	X	X	X	X
Year FE	X	X	X	X
Observations	1,433,010	1,433,010	1,433,010	1,433,010

NOTES: The dependent variable is the fraction of expenditure with deals in the first column, with coupons in the second column, in discount stores in the third column and on large items in the fourth columns. Controls include also the age of the head of household, a dummy equal to one if the head of household is African American, a dummy equal to 1 if the head of household is Hispanic, and finally household size. Standard errors are in parentheses.

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 is 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 in the economy is $\bar{p}_m = \frac{\sum_i x_{im} p_{im}}{\sum_i x_{im}}$. The average quantity purchased of product m in the economy is $\bar{x}_m = \frac{1}{N} \sum_i x_{im}$.

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

$$\sum_{m\in M} p_{im}x_{im} - \sum_{m\in M} \bar{p}_m\bar{x}_m = \sum_{m\in M}(p_{im}-\bar{p}_m)x_{im} + \sum_{m\in M}\bar{p}_m(x_{im}-\bar{x}_m) \tag{1}$$

The first term on the right hand side of (1) highlights price heterogeneity. The larger is the difference between the prices paid by the household and the average prices, the larger will be the difference with $\sum_{m\in M}\bar{p}_m\bar{x}_m$. The second term is due to differences in quantities consumed.

Households typically only consume a fraction of the products available. For this reason, the quantity differences in (1) are in part due to the lack of consumption of some products. In other words, the difference between household i expenditure and $\sum_{m\in M}\bar{p}_m\bar{x}_m$ is partly due to the fact that the household does not consume at all certain products and partly due to the fact that it consumes the other products in a different quantity than the average consumer. We now want to further decompose the second term in (1) into these two additional subcomponents, which we will call composition and quantity heterogeneity. For instance, let's say there are three products in the economy, potatoes, steaks and chips. The average person consumes 2 potatoes, 2 steaks and 2 bags of chips. Paul consumes 0 potatoes, 1 steak and 3 bags of chips. The difference between Paul and the average consumer is due to the fact that Paul consumes less steaks and more chips than the average person and also to the fact that he is not consuming potatoes at all. Formally, we further decompose the second term on the right hand side of (1) as follows

$$\sum_{m\in M}\bar{p}_m(x_{im}-\bar{x}_m) = \sum_{m\in M_i}\bar{p}_m(x_{im}-\bar{x}_m) + \sum_{m\in M_i^c}\bar{p}_m(0-\bar{x}_m) \tag{2}$$

Having established some useful definitions, we can now talk about consumption inequality. Following the previous literature, we divided household consumption by the OECD adult equivalence scale, $S_i = (1+0.7(A_i-1)+0.5K_i)$, where A_i is the number of adults and K_i is the number of children of household i. We define $\hat{x}_{im} = \frac{x_{im}}{S_i}$ and $\tilde{x}_{im} = \sum_i \frac{\hat{x}_{im}}{N}$. We measure inequality as the standard deviation of total annual expenditure:

$$\sqrt{\frac{1}{N-1}\sum_i\left(\sum_{m\in M}p_{im}\hat{x}_{im} - \frac{1}{N}\sum_i\sum_{m\in M}p_{im}\hat{x}_{im}\right)^2} \tag{3}$$

The price adjustment exercise consists in imposing $p_{im} = \bar{p}_m$. We are then left with

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

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

$$= \sqrt{\frac{1}{N-1}\sum_i \left(\sum_{m\in M} \bar{p}_m (\hat{x}_{im} - \tilde{x}_m)\right)^2} \tag{4}$$

We will look at the ratio of (4) to (3) to measure the importance of price heterogeneity in the measurement of consumption inequality. The lower is the ratio, the lower is consumption inequality when measured with the same fixed prices for all consumers. On the contrary, the closer to one is the ratio, the weaker is the impact of price heterogeneity on the measurement of inequality.

When we evaluate the same goods at the average price, consumption inequality reduces to the second term in (1), adjusted with the adult equivalence scale. Following (2), we can further decompose the remaining consumption inequality into quantity and composition heterogeneity

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

$$= \sqrt{\frac{1}{N-1}\sum_i \left(\sum_{m\in M_i} \bar{p}_m (\hat{x}_{im} - \tilde{x}_m) + \sum_{m\in M_i^c} \bar{p}_m (0 - \tilde{x}_m)\right)^2} \tag{5}$$

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

$$\frac{\sqrt{\frac{1}{N-1}\sum_i \left(\sum_{m\in M_i} \bar{p}_m (\hat{x}_{im} - \tilde{x}_m)\right)^2}}{\sqrt{\frac{1}{N-1}\sum_i \left(\sum_{m\in M} \bar{p}_m (\hat{x}_{im} - \tilde{x}_m)\right)^2}} \tag{6}$$

and the share of consumption inequality due to composition heterogeneity

$$\frac{\sqrt{\frac{1}{N-1}\sum_i \left(\sum_{m\in M_i^c} \bar{p}_m(0-\tilde{x}_m)\right)^2}}{\sqrt{\frac{1}{N-1}\sum_i \left(\sum_{m\in M} \bar{p}_m(\hat{x}_{im}-\tilde{x}_m)\right)^2}} \tag{7}$$

Quantity and composition heterogeneity are most likely to be correlated. Households who consume more are likely to consume both higher quantities and a higher number of products. For this reason we expect the covariance to be negative

$$\sum_i [2 \times \sum_{m\in M_i} \bar{p}_m(\hat{x}_{im}-\tilde{x}_m) \times \sum_{m\in M_i^c} \bar{p}_m(0-\tilde{x}_m)] < 0$$

All quantities above will be adjusted using the demographic weights provided by Nielsen.

5 Does price heterogeneity matter?

Table 11: Annual consumption inequality

Dates	Inequality	Barcode Adjusted (%)	BM Adj. (%)	Module Adj. (%)	Group Adj. (%)
2004	934.2	98.6	97.4	96.1	96.0
2005	958.7	98.6	97.4	95.9	96.0
2006	999.4	98.4	96.8	95.2	94.9
2007	1060.1	99.1	98.1	97.3	97.2
2008	1085.9	99.3	98.4	97.7	97.6
2009	1119.0	99.0	97.8	96.4	96.3
2010	1142.9	98.5	97.6	96.4	97.8
2011	1206.2	98.6	97.3	96.3	98.1
2012	1681.2	98.2	97.7	97.0	96.7

Source: Nielsen and own calculations. Inequality is measured as the standard deviation of the annual household consumption adjusted with the adult equivalence scale. The adjusted consumption inequality is reported as a percentage of the true consumption inequality. The demographic weights provided by Nielsen are used in the computations.

We now try to address the main research question of the paper. Does price heterogeneity matter for the measurement of consumption inequality? As explained in the previous section, we compare consumption inequality measured with actual prices and consumption inequality measured with fixed prices equal for all consumers. We first compute the average price paid for each product in the United States during each year. We then impose that such average price is used to compute annual household expenditure. Finally, we compute consumption inequality as the standard deviation of annual consumption adjusted with the adult equivalence scale. We do this for the four levels of product definition described in Section 3, barcode, BM, module and group.

Table 11 reports the actual inequality and the ratios of (4) to (3) in percentages. We find that adjusted inequality is on average 1% lower than "true" inequality, when the adjustment is made at the barcode level, and at most 5% 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. Similar results are found if consumption inequality is measured as the standard deviation of the logarithm of annual expenditure or as other measures of statistical dispersion.[7]

6 Quantity vs composition

Table 12: Average Number of UPCs by Income

	Top 10%	Bottom 10%
2004	656	410
2005	678	409
2006	666	392
2007	693	363
2008	690	356
2009	661	350
2010	651	350
2011	681	352
2012	720	357

Source: Nielsen and own calculations.

If price heterogeneity is not relevant for consumption inequality, it must be that quantity and composition heterogeneity explain most of the inequality in the data. In Table 12, we

[7] We experimented with the 90-10, 90-50 and 50-10 ranges and the results are very similar.

report the average number of distinct barcode-level products purchased by households in the top and bottom 10% of the income distribution. These statistics provide some evidence on the composition of consumptions baskets, but do not include any information on the quantities consumed by the households. Table 12 shows that rich households purchase on average 80% more distinct products than poor households, and therefore provides some evidence of a composition factor behind consumption inequality.

Table 13: Quantity versus composition

	UPC		BM		Module		Group	
	(6)	(7)	(6)	(7)	(6)	(7)	(6)	(7)
2004	2.1	1.9	1.9	1.6	1.3	1.0	1.0	0.4
2005	2.1	1.8	1.9	1.6	1.3	1.0	1.0	0.4
2006	2.1	1.8	1.9	1.6	1.3	1.0	1.0	0.4
2007	2.1	1.7	1.8	1.5	1.3	1.0	1.0	0.4
2008	2.0	1.7	1.8	1.5	1.3	0.9	1.0	0.4
2009	2.0	1.7	1.8	1.5	1.3	0.9	1.0	0.4
2010	2.0	1.7	1.8	1.5	1.3	0.9	1.0	0.4
2011	1.9	1.7	1.8	1.5	1.3	0.9	1.0	0.4
2012	1.7	1.4	1.6	1.2	1.2	0.8	1.0	0.4

Source: Nielsen and own calculations. (6) measures the share of consumption inequality due to quantity heterogeneity and (7) due to composition heterogeneity. The ratios (6) and (7) are computed for each product definition level.

This evidence prompts us to further decompose consumption inequality into its quantity and composition components, as explained in Section 4. Table 13 reports the measures of the relative importance of quantity and composition heterogeneity described in (6) and (7). 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 (6) and (7) are always higher than 1. 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 of consumption inequality is due to quantity heterogeneity.

7 Concluding Remarks

We address the important question of whether inequality measured in real terms is lower than in nominal terms. There is plenty of evidence, confirmed by our analysis, 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. This result suggests that researchers must be careful when aggregating products.

Most importantly, this paper provides useful evidence for the debate 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 is a factor reducing the impact of rising wage and income inequalities on well-being inequality, as suggested by some recent studies.

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