Prices are Higher in Poor Markets*

Matías Brum[†], Iael Klaczko[‡] and Leandro Zipitría[§]

This version: June 6, 2024

Abstract

We study the income elasticity of prices. On aggregate, there seems to be no relation between prices and neighborhood or department—markets—prices. When grouped by income quartiles, differences emerge. The poorest quartiles pay between 2.7 to 4.2 % more than quartiles two and three. The richest quartile pays between 9.8 to 14.5% less than the control quartiles. The interaction of income to our dummy quartile shows that prices are higher among the poorest of the poor quartile and among the wealthiest in the richest quartile. While the analysis has caveats, price discrimination of the poor seems to be the case in Uruguay.

JEL CODES: D31, E63, D63, L1, L81.

Keywords: Price Dispersion, Market Segmentation, Inequality.

*We thank the Consumer Defense Unit of the Uruguayan Ministry of Economy and Finance—especially Alejandro Mateos and Gabriela Carrasco—for granting access to the supermarket price database and to Scanntech—especially to Martín Severgnini—for providing the grocery price database. We thank Fernando Borraz for comments and suggestions. All errors remaining remain ours.

[†]Universidad ORT Uruguay.

[‡]Departamento de Economía, Facultad de Ciencias Sociales, Universidad de la República. iael.klaczko@cienciassociales.edu.uy

[§]Departamento de Economía, Facultad de Ciencias Sociales, Universidad de la República. leandro.zipitria@cienciassociales.edu.uy

1 Introduction.

Do people experiencing poverty pay more for their products? This is an empirical question that has been studied in economics for a long time. The pioneering work of Caplovitz (1963) showed that the poor earn less and pay more for the same products than the rich people in the US. We address this question for Uruguay, a 3.5 million inhabitants high-income country in Latin America, where 7% of the households are poor, and the Gini coefficient is 0.394 according to 2023 poverty and inequality reports of the Uruguayan *Instituto Nacional de Estadística (INE)*.[1].

In the ideal setting, we would like to compare the purchases of individuals and families across different places in the income spectrum to determine whether prices for the same products are higher for low-income families. Such data is not currently available in Uruguay. Instead, we have a detailed—and extensive—database of posted prices from nearly all supermarkets in Uruguay, supplemented by another database with data on prices from small grocery stores. We can then compare the prices of the products in the database to determine whether they are higher in poor neighborhoods, i.e., whether people with low incomes are exposed to higher prices instead of paying higher ones. To our knowledge, this is the first paper that addresses such a question in Latin America.

We present the main empirical strategy in Section 3. First, we study the income elasticity of prices by regressing the prices of identical products in stores to the income of the neighborhood or department—in Spanish, *departamento*—where the store is located. We perform several controls to check the robustness of the estimations. The literature has emphasized that consumers respond differently to price shocks by their income level; i.e., preferences are non-homothetic (Handbury (2021) and Jaravel and Lashkari (2023)).

Then, we allow for greater flexibility in the estimation. First, we classify each market—i.e., neighborhood or department—into a monthly income quartile according to its average income. Then, we group quartiles 2 and 3 into a "middle-class" group to compare how prices in the top and bottom quartiles respond to cross-section income differences. Third,

[1] INE (2023a), page 1, INE (2023b), Table 1, page 1.

we run a regression for the (log-deflated) product price to the neighborhood (log-deflated) income with a twist: we interact the income parameter to a dummy equal one if the neighborhood is in the first quartile and another dummy equal one if the neighborhood income is at the fourth quartile.

Our results show that the income elasticity of prices is U-shaped, with higher prices charged for the poorest among the poor quartile and the wealthiest in the richest quartile. The poorest quartiles pay between 2.7 to 4.2 % more than quartiles two and three. The richest quartile pays between 9.8 to 14.5% less than the control quartiles. The interaction of income to our dummy quartile shows that prices are higher among the poorest of the poor quartile and among the wealthiest in the richest quartile. Entry of new stores has a moderating effect on the result, but it remains significant. More competition, as measured by the number of stores in the market, implies higher prices in the poor quartile markets.

The literature is not unanimous on whether poor households pay more. For example, Gibson and Kim (2013) found that low-income neighborhoods have lower prices than the rest of Vietnam, Blow and Leicester (2012) found that more affluent households in Britain pay more than poor ones, while Broda, Leibtag, and Weinstein (2009) using consumer purchases found that people experiencing poverty pay less. Why do people experiencing poverty pay less? Beatty (2010) found that people experiencing poverty pay less because they buy more items at quantity discounts, while Broda, Leibtag, and Weinstein (2009) found that the poor pay less than the richer ones, mainly by shopping for items on sale.

On the contrary, Rao (2000) in rural India and Attanasio and Frayne (2006) in rural Colombia found the opposite result. People experiencing poverty pay more for similar products because income restrictions force them to buy small quantities of products. The relative income dispersion of the neighborhoods also affects prices. Frankel and Gould (2001) found that great income inequality in poor—but also rich—neighborhoods increases prices compared to more income-equal ones. Chung and Myers (1999) show that people experiencing poverty pay more if they buy in independent stores. Consumer inertia may also influence consumption (Bronnenberg, Dube, and Gentzkow (2012)). Owens (2019) showed that consumers pay more when they move to a new location. Finally, poor people may have access to different baskets of products than richer ones. Handbury (2021) found that more affluent cities have a large variety of products that result in consumers having 40% more utility from their purchases than citizens in poor cities in the US.

A related literature studied how macroeconomic shocks impact consumers according to their income. Jaravel (2019) showed that people at the lowest quintile have experienced higher inflation in the US, mainly due to richer ones having access earlier to newer products. Large devaluations may also hurt people with low incomes. Cravino and Levchenko (2017) showed that after the 1994 devaluation of the Mexican peso, the prices of the bottom decile increased 1.5 times higher than the top decile after two years.[2]

The paper is organized as follows. The next Section presents the data. Section 3 shows the paper's main results. Section 4 shows additional controls to the main estimation to check whether additional differences exist between markets. Section 5 concludes.

2 Data.

We have access to a grocery price database collected by the Uruguayan Ministry of Economy and Finance's General Directorate of Commerce (*Dirección General de Comercio*, DGC). It is an unbalanced panel for 125 supermarket products. All products were selected to be comparable between stores and mainly represent the three most-selling brands in each product category chosen. This database has been previously used in Borraz and Zipitría (2012) to characterize price rigidity, Borraz, Cavallo, Rigobon, and Zipitría (2016) and Borraz and Zipitría (2022) to study price convergence, and Borraz and Zipitría (2024) for analyzing demand shocks and store's price responses. Stores that meet criteria in size—have at least three cashiers—or the number of stores within the same commercial name, and the share of products listed by the DGC have to report their daily prices each month.

[2]For more evidence on "inflation inequality," see Jaravel (2021).

The database has daily price information from April 2007 to December 2022. We calculate the monthly price average for each product and store. Then, we deflate each price by the general monthly Consumer Price Index (CPI) to obtain real prices. The database has information on each store's location and the number of cashiers—i.e., proxy of size. We have nearly 5 million price observations.

We combine this information with income data at the market level published by the *Instituto Nacional de Estadísticas* (National Institute of Statistics, INE) in Uruguay. Markets are defined as each neighborhood for the capital city Montevideo, and each department—*departmento*—for the rest of the country. Most cities outside Montevideo do not have enough observations to create a reliable measure of income. Also, we compute income by calculating the moving quarter's average for each market to gain enough observations and mitigate outliers. Finally, we deflate the average income by the monthly CPI.

For each month, we assign each market to an income quartile. Markets may change in their quartile distribution across time. While we are interested in the income elasticity of prices, we want to know if this elasticity may be non-monotonic. That is if prices have a non-linear relation to the market income. For comparison, we pick the first and fourth quartile, being both the second and third omitted in the estimations. Table 1 shows the summary statistics for the database.

Some evidence provide support for our strategy. According to the "*Encuesta Nacional de Gastos e Ingresos de los Hogares 2016-2017*" (National Survey of Household Income and Expenditures for 2016-2017) from the Uruguayan *Instituto Nacional de Estadística* the households at the first income decile spend twice their income in food and non-alcoholic beverage than the tenth decile.[3] This very relevant difference in the spending weight in these products makes it necessary to account for non-linearity in income on the price of products.

Table 1 shows that, on average, real prices for the first and fourth quartile seem similar

[3]INE (2017), Table 31, page 80.

Table 1: Summary Statistics.

Sample Period	04/2007		12/2022	
Number of Observations	4,940,552			
Number of Stores	539			
Number of Chains	23			
Number of Markets (location)	67			
Number of Products	125			
Number of Categories	42			
	Quartile 1		Quartile 4	
	Mean	St. D	Mean	St. D
CPI Adjusted Log Price	3.2651	0.5475	3.2860	0.5470
CPI Adjusted Income▲	9,218	1,270	21,164	5,170
Number of Stores	216.18	138.16	241.45	207.88
Number of Products	76.07	46.03	75.80	46.32
Number of Observations	908,883		1,680,662	

Notes: Except for Consumer Price Index (CPI) adjusted Log Price, mean, and standard deviation for variables are calculated for the time-market data.
CPI base year is 2022. Prices are referred to April 2007.
▲Income is in December 2010 pesos.

to the average number of products at the stores. Nevertheless, richer quartiles have 20% more stores to buy for. Lastly, the real income for markets in the first quartile is less than half that of those in the richer quartile. Also, the standard deviation of incomes shows that the dispersion is twice as large in the wealthiest quartile than in the poorest.

3 Empirical Strategy.

We want to study how supermarket prices relate to market income. That is, if there are cross-sectional price differences between stores due to neighborhood or department income differences. As a baseline, we compare the (deflated) prices of the products in our basket across markets. Our main task is to estimate the income elasticity of prices, with income being the real income of each market. We estimate the following equation:

$$p_{it}^{sm} = \alpha + \beta I_t^m + \gamma X_{it}^{sm} + \epsilon_{it}^m, \tag{1}$$

Table 2: Income Baseline Estimation.

Dependent Variable:	log Deflacted Price						
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
log Income	0.0384***	-0.0010***	0.0182**	-0.0019***	0.0013***	0.0021***	0.0017***
	(1×10^{-5})	(1×10^{-5})	(0.0082)	(1×10^{-5})	(1×10^{-5})	(1×10^{-5})	(1×10^{-5})
Fixed-effects							
Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market		Yes		Yes	Yes	Yes	Yes
Product			Yes	Yes	Yes	Yes	Yes
Chain					Yes		
Store						Yes	Yes
Product x Store							Yes
Fit statistics							
Observations	4,880,761	4,880,761	4,880,761	4,880,761	4,880,761	4,880,761	4,880,761
R^2	0.00341	0.00514	0.93736	0.93828	0.93942	0.94029	0.94767
Within R^2	0.00059	3.1×10^{-8}	0.00208	1.63×10^{-6}	7.86×10^{-7}	2.15×10^{-6}	1.51×10^{-6}

Clustered (Category & Chain) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Where p_{it}^{sm} is the log CPI adjusted price of product i in time t in store s and market m, I_t^m is the log CPI adjusted income of market m in time t, and X_{it}^{sm} are product, time, market, chain or store dummies. The next Table shows the results of the estimation of Equation 1.

Table 2 shows that prices and income seem to have a positive relationship: when income increases, prices also increase. That is, wealthier people pay higher prices. Column (1) shows the result with only time dummies as controls, and results show a 3.8 percent income elasticity of prices. Next, we add market dummies to control for specific characteristics of markets—such as differences in public transport or the sparsity of the city/neighborhood—and the income elasticity sign turns negative and with low economic value. Column (3) shows the results of adding product dummies to control for differences in prices and the availability of products due to their characteristics (Handbury and Weinstein (2015)), and income elasticity is positive again. Also, note the sharp increase in the explanatory power of the regression. Controlling by differences in products decreases the magnitude of the effect to nearly 2%, so differences between markets may also be explained by differences in baskets (Handbury (2021)).

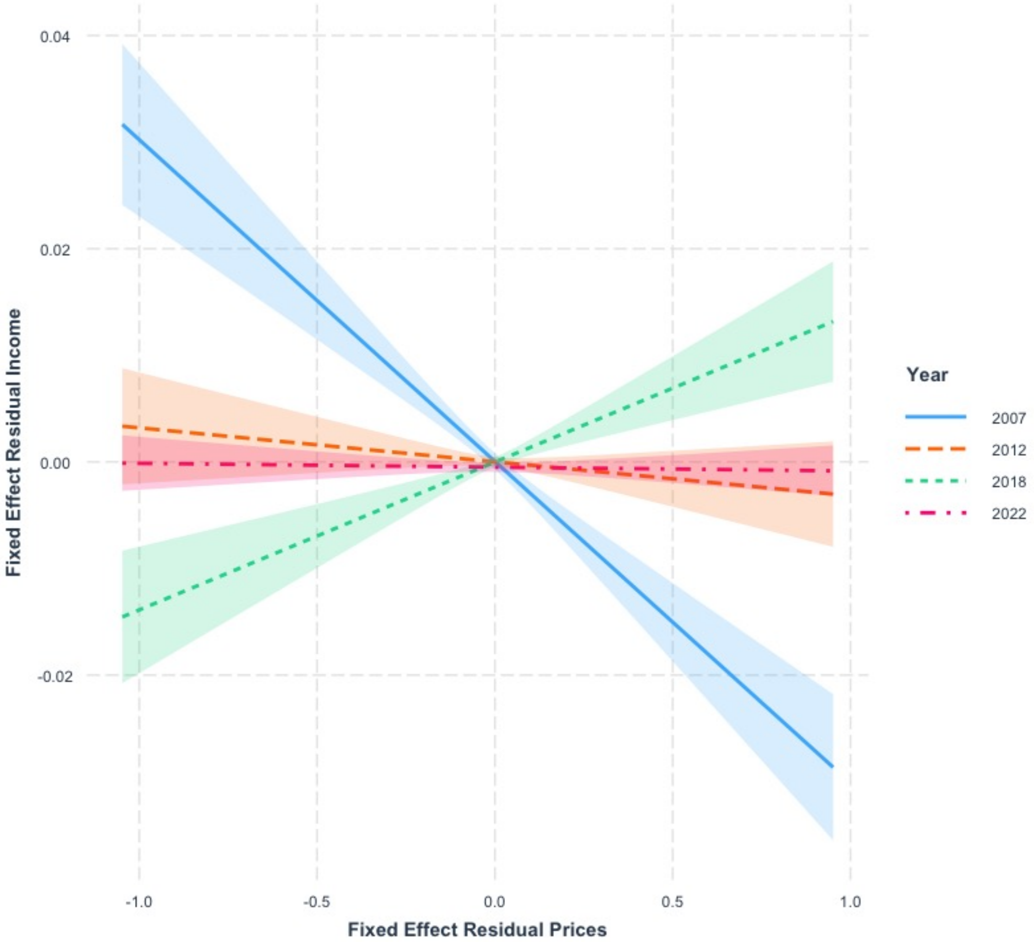
In Column (4), we add product and market dummies to check which effect is stronger, and income elasticity returns to negative. Column (5) adds a chain dummy to control for pricing being subject to uniform chain policies (DellaVigna and Gentzkow (2019)) and the income elasticity return to positive. This will be our preferred estimation, as there are enough controls for distinctive characteristics that may affect the estimation of the income elasticity. In columns (6) and (7), we add the store and product-store dummies to further control for differences in store assortment, management decisions, pricing policies, etc. Our elasticity estimation remains positive, and its value increases with these additional controls.

Nevertheless, previous results seem inconsistent, as the sign flips between positive and negative. Also, the value of the income elasticity estimation is economically small: less than 1%. As the data is an unbalanced panel, the change in the estimated coefficient may be due to new stores entering the sample. We repeat our estimations but only for the stores in the year 2007 throughout the sample. Table 8 in Appendix A shows that most of the changes in the income elasticity sign are due to the entry of new stores. The effects remain economically negligible. While new stores explain the changes in the coefficient sign, it does not seem to drive the significance of our results.

The entry of stores into the market may change the results over time. Our database encompasses nearly sixteen years of data. Then, there should be changes across time that may explain the negligible impact found. The following Figure plots the estimation of the income elasticity interacted with the year variable for selected years. It shows how the income elasticity has changed from being strongly negative in 2007 to being positive in 2018 and to being zero in 2022.

Then, the negligible result may be because the cross-section change in income elasticity has also changed over time. Or it may be the case that our linear income specification does not adequately capture the effect of income on prices. In particular, the literature

Figure 1: Income Price Elasticity by Year.



has emphasized the role of non-homothetic preferences, i.e., non-linearities of income to consumption decisions ((Handbury, 2021), (Jaravel and Lashkari, 2023)).

Due to the small number of markets, we group each by income quartile for each month in the sample for every period. Jaravel (2019), for example, group individuals by income quintiles. As we do not have information on individuals—for purchases or income—we grouped stores in a market by the income quartile of the market. We modify Equation 1 by adding two dummies for the lowest and highest quartile and interact each one with the real Log CPI adjusted income, quartiles two and three the omitted ones, as shown next:

$$p_{it}^{sm} = \alpha + \alpha_1 Q_1 + \alpha_4 Q_4 + \beta I_t^m + \beta_1 Q_1 I_t^m + \beta_4 Q_4 I_t^m + \gamma X_{it}^{sm} + \epsilon_{it}^m. \quad (2)$$

Where Q_1 and Q_4 are the first and fourth quartiles respectively.

Equation 2 allows for a flexible relationship between prices and income in a given market. If income has a non-linear relationship with prices, then β_1 and β_4 should differ from zero. The following Table shows the results of the estimation of Equation 2. Estimations are weighted by the number of observations in each quartile.

Table 3 shows a different picture from Table 2. First, as previously mentioned, most of the variance in prices is explained by differences in the price of products, i.e., when product-dummies are added. Secondly, the results confirm that the income elasticity of prices is non-linear. In our preferred estimation, Column (5), the first quartile has prices 2.74% higher than the omitted quartiles. In turn, the fourth quartile has prices 14.52% lower than the omitted quartiles. If we add additional controls, Column (7), the price premium of the lower quartile doubles, and the price benefit of the higher reduces.

More interestingly, the interactions between (log real) income and the quartile dummy show that prices are higher for the poorest in the first quartile and for the richest in the highest quartile. One standard deviation of income in the first quartile—1,270—decreases prices by 12.5%.[4] In turn, for the richer quartile, an increase in one standard deviation of income—5,170—increases prices by 43%.[5] These are huge variations within quartiles.

Note that the income elasticity of prices is U-shaped. The poor have a fixed difference in prices 2.7-4.2% higher, and the rich have prices 9.6-14.5% lower than the middle class. Also, within each quartile, the effect decreases for the first quartile and increases for the fourth.

Next, we provide a similar figure to 1, but now for the interaction between the first and fourth quartile dummy with the year dummy. For simplicity, we omit the interaction of quantiles with income.

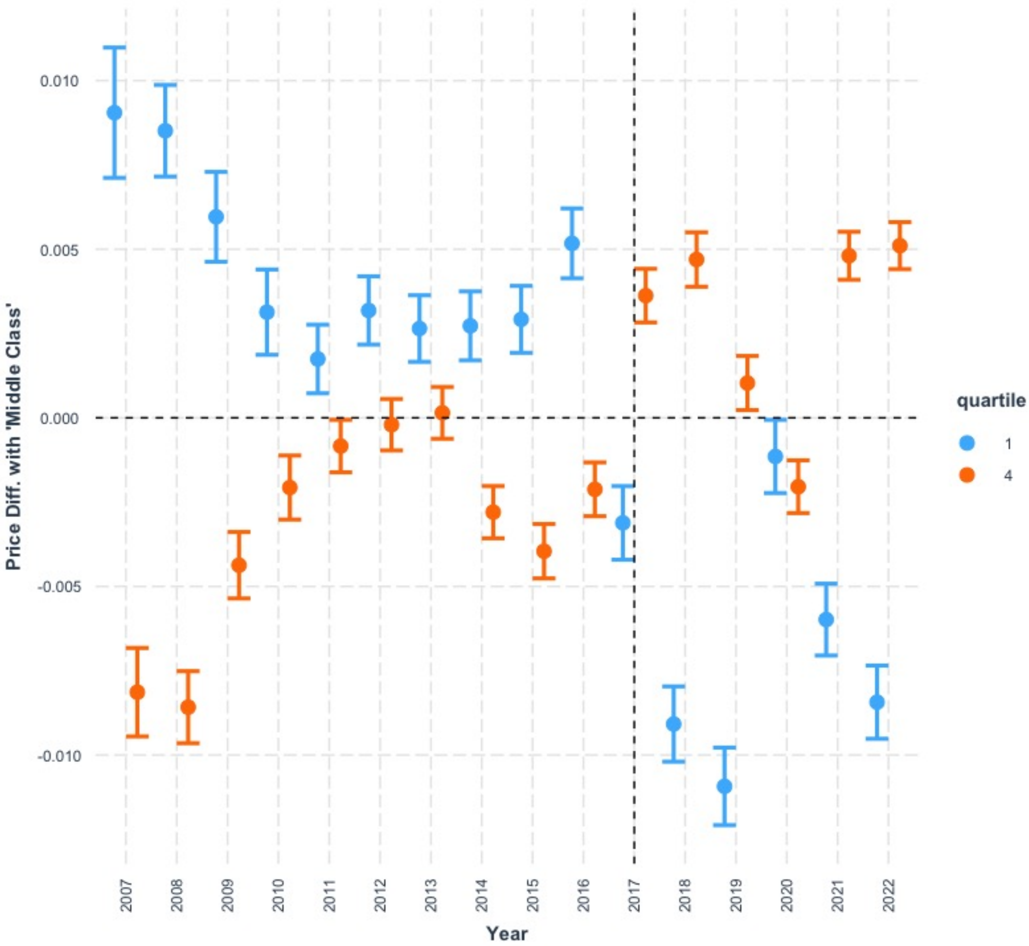
[4]This is 1,270 times -0.0098, that is -0.0067-0.0031, which equals 12.45%.
[5]The result of 5,170 times 0.0083, or 0.015 - 0.0067.

Table 3: Income Quartile Interaction Estimation.

Dependent Variable:	log Deflacted Price						
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
log Income	0.0269***	-0.0127***	0.0173	-0.0094***	-0.0067***	-0.0049***	-0.0030***
	(1.36×10^{-5})	(0.0005)	(0.0130)	(0.0016)	(0.0016)	(0.0006)	(0.0006)
First Quartile	0.1895***	0.1067***	0.0512	-0.0244	0.0274**	0.0285	0.0422***
	(5.17×10^{-5})	(3.42×10^{-5})	(0.1270)	(0.0271)	(0.0118)	(0.0255)	(0.0137)
Fourth Quartile	-0.3056***	-0.2284***	-0.1156	-0.1641***	-0.1452***	-0.1357***	-0.0975***
	(1.01×10^{-5})	(8.53×10^{-5})	(0.1225)	(0.0270)	(0.0101)	(0.0228)	(0.0173)
log Income × First Quartile	-0.0207***	-0.0119***	-0.0052	0.0025	-0.0031***	-0.0032	-0.0047***
	(0.0005)	(0.0003)	(0.0132)	(0.0029)	(0.0011)	(0.0026)	(0.0013)
log Income × Fourth Quartile	0.0311***	0.0235***	0.0115	0.0168***	0.0150***	0.0140***	0.0100***
	(2.61×10^{-5})	(0.0005)	(0.0128)	(0.0027)	(0.0010)	(0.0023)	(0.0018)
Fixed-effects							
Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market		Yes		Yes	Yes	Yes	Yes
Product			Yes	Yes	Yes	Yes	Yes
Chain					Yes		
Store						Yes	Yes
Product x Store							Yes
Fit statistics							
Observations	4,880,761	4,880,761	4,880,761	4,880,761	4,880,761	4,880,761	4,880,761
R^2	0.00350	0.00517	0.93742	0.93832	0.93946	0.94031	0.94767
Within R^2	0.00069	8.42×10^{-6}	0.00253	6.43×10^{-5}	4.58×10^{-5}	4.31×10^{-5}	2.87×10^{-5}

Clustered (Category & Chain) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Figure 2: Prices by Income Quartile by Year.



The plot shows the huge price gap between the first and fourth quartiles, as well as how the gap closes in time and reverses by the year 2017. We now present several robustness checks to our results. The Tables show the results for our preferred estimation, the one with time, product, market, and chain control dummies and the full control dummies.

First, we estimate Equation 2 for the stores in 2007; that is, we exclude entry. Table 4 shows that the U-shaped results remain. The dummy variable for the first quartile is twice higher and the dummy variable for the fourth quartile 25% less than in Column (5) of Table 3. Also, the interaction effect is twice as large for the first quartile and lower for the fourth quartile than in Table 3. The U-shaped results are larger when the sample considers the same stores. Entry seems to favor people experiencing poverty.

Next, we split the sample between chains and independent stores. DellaVigna and

Table 4: Income Quartile Interaction Estimation. Sample of Stores from Year 2007.

Dependent Variable:	log Deflacted Price	
Model:	(1)	(2)
Variables		
log Income	-0.0042*	-0.0020
	(0.0021)	(0.0014)
First Quartile	0.0553***	0.0731***
	(2.85×10^{-5})	(1.75×10^{-5})
Fourth Quartile	-0.1100***	-0.0915***
	(0.0003)	(0.0002)
log Income × First Quartile	-0.0061***	-0.0080***
	(6.69×10^{-5})	(6.25×10^{-5})
log Income × Fourth Quartile	0.0113***	0.0094***
	(8.86×10^{-5})	(2.91×10^{-5})
Fixed-effects		
Product	Yes	Yes
Time	Yes	Yes
Chain	Yes	
Market	Yes	Yes
Store		Yes
Product x Store		Yes
Fit statistics		
Observations	3,561,465	3,561,465
R^2	0.94225	0.94783
Within R^2	3.42×10^{-5}	3.21×10^{-5}

Clustered (Category & Chain) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Gentzkow (2019) for the US and Borraz and Zipitría (2024) for Uruguay have shown that stores within the same chain have uniform prices. Table 5 shows the result of the estimation of Equation 2 for the two samples: chains and independent stores. For chains, standard errors are clustered at the chain and category level, and at the while for independent stores, at the category level, and weights are the number of observations for each quartile in each subsample.

Table 5 shows that the signs of the income elasticity of chains and independent stores are opposite. The insignificance of the estimated coefficients for the independent stores may be due to clustering, which changes between columns and concerning Table 3. The

Table 5: Income Quartile Interaction Estimation. Split Sample: Chains and Independent Stores.

Dependent Variable:	log Deflacted Price			
By:	Chains		Indep. Stores	
Model:	(1)	(2)	(3)	(4)
Variables				
log Income	-0.0086**	-0.0054*	0.0112**	0.0176***
	(0.0038)	(0.0029)	(0.0046)	(0.0043)
First Quartile	-0.0382**	-0.0246***	0.0621	0.0946*
	(0.0139)	(0.0036)	(0.0620)	(0.0544)
Fourth Quartile	-0.1733***	-0.1259***	0.0652	0.1218**
	(0.0428)	(0.0301)	(0.0551)	(0.0505)
log Income × First Quartile	0.0039***	0.0025***	-0.0067	-0.0101*
	(0.0013)	(0.0002)	(0.0067)	(0.0059)
log Income × Fourth Quartile	0.0180***	0.0130***	-0.0069	-0.0129**
	(0.0044)	(0.0030)	(0.0058)	(0.0053)
Fixed-effects				
Product	Yes	Yes	Yes	Yes
Chain	Yes		Yes	
Time	Yes	Yes	Yes	Yes
Market	Yes	Yes	Yes	Yes
Store		Yes		Yes
Product x Store		Yes		Yes
Fit statistics				
Observations	3,707,276	3,707,276	1,173,485	1,173,485
R^2	0.94031	0.94733	0.94107	0.95616
Within R^2	6.59×10^{-5}	4.16×10^{-5}	2.87×10^{-5}	7.86×10^{-5}

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

income elasticity is negative for chains and positive for independent stores. Interestingly, there does not seem to be a robust difference between quartiles for independent stores. For chains, prices for the first quartile are 2.4-3.8% lower, and for the fourth quartile there are 12.6-17.3% lower than the omitted quartiles. Also, the interaction of quartiles to income shows a positive sign that, added to the income parameter, turns positive the sign for the fourth quartile but remains negative for the first one. The U-shape income elasticity is clear for chains, less so for independent stores. The cross-section change in income elasticity results from differences in pricing policies between chains and independent stores.

4 Additional Explanations.

Previously, we explored the role of chains in explaining differences in the income elasticity of prices. Table 5 showed that independent stores set prices higher as income increases, but chains charge more to the middle class. We attempt additional explanations for these differences in the response of prices to income.

Why are prices for the poorest and wealthiest people higher than in between? Not a single explanation could do both. First, the basket of products available in the more affluent neighborhoods may be of higher quality, so prices could be higher. If stores in the wealthier neighborhoods sold olive oil and soy oil in the poorest neighborhoods, then prices would be higher because the products differed. Handbury and Weinstein (2015) showed that the basket of products varies between US cities, and so do prices. Second, it could be the case that stores in the poorest markets have less competition or fewer varieties available. In both cases, prices could be higher due to less store competition or product competition—i.e., fewer products are available on the shelf.

In the following analysis, we add several controls to Equation 2 such as the number of cashiers of the store—a proxy for size—, the number of competitors in the market—as a share of per thousand population—, and the share of products at the store, as a measure of product store.

Table 6 shows the interaction of our three controls with the dummy quartiles. First, when the controls are added, most of the differences vanish. Secondly, the size of the stores—measured by the number of cashiers—does not play a role. For the richest, having access to more goods at the store implies lower prices, broadly in line with Jaravel (2019). Finally, the higher the number of competing stores for the lower quartile, the higher the prices. This is an interesting result, as the opposite sign should be expected. Nevertheless, this should not be the case if stores in the wealthiest markets are larger, resulting in fewer stores. Then, if in the poorest market, stores are smaller and there are a large number, then prices could be higher. Interestingly, results do not change substantially when the entry of stores is not considered; see the results in Table 9 in Appendix A.

Lastly, in Table 7, we split the sample between chains and independent stores and added the controls. The income elasticity is positive for independent stores, but no quartile differences exist. The first quartile dummy is strongly significant for chains, as it is the interaction between income and the first—negative—and fourth—positive—quartile. Interestingly, more products mean higher prices for chains, while the opposite is true for the wealthier quartile. More competition, as measured by the number of stores per thousand inhabitants, implies higher prices for chains and independent stores for the poor, with mixed results for the wealthiest quartile. For independent stores, larger ones imply lower prices for the poor and higher for the wealthiest quartiles.

5 Conclusion.

This paper studies how prices relate to the neighborhood or department income. While the effect of income seems null on aggregate, the result hides non-linearities along the income path. When markets are grouped by quartile, a different picture emerges. We found that people experiencing poverty pay more, even when controlling for several fixed effects. The entry of new stores has not changed the result, although some moderating effect is found. Interestingly, in poor markets, more competition implies higher prices. This may be because there could be more small stores that charge higher prices.

There are several caveats to our results. First, we do not have access to actual purchases but must rely on the market's aggregate income. Our results do not imply that people experiencing poverty pay more but are exposed to higher relative prices in their neighborhoods. Secondly, we have a pre-defined basket of products that may not adequately represent the purchases of consumers. That is, they may purchase products that are not among those bought and bias our results. While this may be the case, this caveat does not change our main point: low-income people are exposed to higher prices.

Table 6: Income Quartile Estimation. Additional Controls.

Dependent Variable:	log Deflacted Price	
Model:	(1)	(2)
Variables		
log Income	-0.0009	2.9×10^{-5}
	(0.0016)	(0.0027)
Num. Cashiers	6.47×10^{-5}	1.580
	(0.0002)	(1,936,773.4)
Sh. Prod. at Store	0.0139	-0.0142
	(0.0165)	(0.0199)
Num. Compet. per (1,000) Pop.	0.0199	-0.0068
	(0.0246)	(0.0116)
First Quartile	0.0372	0.0019
	(0.0385)	(0.0138)
Fourth Quartile	-0.0379	-0.0312
	(0.0250)	(0.0200)
log Income × First Quartile	-0.0041	-0.0019
	(0.0026)	(0.0017)
log Income × Fourth Quartile	0.0084***	0.0071***
	(0.0019)	(0.0023)
Num. Cashiers × First Quartile	-0.0007	-0.0005
	(0.0005)	(0.0005)
Num. Cashiers × Fourth Quartile	-0.0003	0.0004**
	(0.0003)	(0.0002)
Sh. Prod. at Store × First Quartile	0.0023	0.0224
	(0.0227)	(0.0160)
Sh. Prod. at Store × Fourth Quartile	-0.0559***	-0.0577***
	(0.0084)	(0.0162)
Num. Compet. per (1,000) Pop. × First Quartile	0.0361***	0.0315***
	(0.0072)	(0.0037)
Num. Compet. per (1,000) Pop. × Fourth Quartile	-0.0054	0.0099
	(0.0198)	(0.0127)
Fixed-effects		
Product	Yes	Yes
Chain	Yes	
Time	Yes	Yes
Market	Yes	Yes
Store		Yes
Fit statistics		
Observations	4,880,761	4,880,761
R^2	0.93949	0.94035
Within R^2	0.00057	0.00073

Clustered (Category & Chain) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 7: Income Quartile Estimation. Additional Controls. Sample Split by Chains and Independent Stores.

Dependent Variable:	log Deflacted Price			
By:	Chains		Indep. Stores	
Model:	(1)	(2)	(3)	(4)
Variables				
log Income	-0.0033	-0.0009	0.0123***	0.0115**
	(0.0039)	(0.0044)	(0.0044)	(0.0048)
Num. Cashiers	0.0002	4.358	-0.0006***	11.98
	(0.0002)	(8,491,634.2)	(0.0001)	(700,515.1)
Sh. Prod. at Store	-0.0105	-0.0057	0.0496***	-0.0381***
	(0.0191)	(0.0179)	(0.0109)	(0.0123)
Num. Compet. per (1,000) Pop.	-0.0092	-0.0056	0.0534***	0.0067
	(0.0139)	(0.0193)	(0.0138)	(0.0121)
First Quartile	-0.0713***	-0.0672***	0.0912	0.0560
	(0.0028)	(0.0013)	(0.0555)	(0.0564)
Fourth Quartile	-0.0639	-0.0397	0.0649	0.0258
	(0.0457)	(0.0405)	(0.0501)	(0.0522)
log Income × First Quartile	0.0050***	0.0046***	-0.0064	-0.0059
	(0.0012)	(0.0014)	(0.0063)	(0.0062)
log Income × Fourth Quartile	0.0108**	0.0087*	-0.0042	-0.0051
	(0.0047)	(0.0047)	(0.0054)	(0.0058)
Num. Cashiers × First Quartile	-0.0004	-0.0002	-0.0006	-0.0013**
	(0.0003)	(0.0008)	(0.0006)	(0.0005)
Num. Cashiers × Fourth Quartile	-0.0002	0.0006	0.0001	0.0006***
	(0.0002)	(0.0012)	(0.0002)	(0.0001)
Sh. Prod. at Store × First Quartile	0.0336**	0.0322*	-0.0410***	0.0045
	(0.0137)	(0.0169)	(0.0116)	(0.0099)
Sh. Prod. at Store × Fourth Quartile	-0.0570***	-0.0723***	-0.0245**	0.0253*
	(0.0078)	(0.0078)	(0.0109)	(0.0146)
Num. Compet. per (1,000) Pop. × First Quartile	0.0312***	0.0268***	0.0374**	0.0291**
	(0.0072)	(0.0064)	(0.0143)	(0.0128)
Num. Compet. per (1,000) Pop. × Fourth Quartile	0.0100	0.0104**	-0.0616***	-0.0080
	(0.0125)	(0.0050)	(0.0132)	(0.0129)
Fixed-effects				
Product	Yes	Yes	Yes	Yes
Chain	Yes			
Time	Yes	Yes	Yes	Yes
Market	Yes	Yes	Yes	Yes
Store		Yes		Yes
Fit statistics				
Observations	3,707,276	3,707,276	1,173,485	1,173,485
R^2	0.94036	0.94050	0.94115	0.94229
Within R^2	0.00088	0.00096	0.00136	0.00038

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

References

Attanasio, O., and C. Frayne (2006): "Do the Poor Pay More?," Working Paper Series 06-06, The Mario Einaudi Center for International Studies.

Beatty, T. K. (2010): "Do the Poor Pay More for Food?," *American Journal of Agricultural Economics*, 92(3), 608–621.

Blow, L., and A. Leicester (2012): "Do the Poor Pay More? An Investigation of British Grocery Purchase Prices," Working paper series, Institution for Fiscal Studies.

Borraz, F., A. Cavallo, R. Rigobon, and L. Zipitría (2016): "Distance and Political Boundaries: Estimating Border Effects under Inequality Constraints," *International Journal of Finance & Economics*, 21(1), 3–35.

Borraz, F., and L. Zipitría (2012): "Retail Price Setting in Uruguay," *Economia*, 12(2), 77–109.

——— (2022): "Varieties as a Source of Law of One Price Deviations," *International Economics*, 172, 1–14.

——— (2024): "Assessing Long-Run Price Convergence in Retailing," Discussion paper.

Broda, C., E. Leibtag, and D. E. Weinstein (2009): "The Role of Prices in Measuring the Poor's Living Standards," *Journal of Economic Perspectives*, 23(2), 77–97.

Bronnenberg, B. J., J.-P. H. Dube, and M. Gentzkow (2012): "The Evolution of Brand Preferences: Evidence from Consumer Migration," *American Economic Review*, 102(6), 2472–2508.

Caplovitz, D. (1963): *The Poor Pay More*. The Free Press.

Chung, C., and S. L. Myers (1999): "Do the Poor Pay More for Food? An Analysis of Grocery Store Availability and Food Price Disparities," *The Journal of Consumer Affairs*, 33(2), 276–296.

Cravino, J., and A. A. Levchenko (2017): "The Distributional Consequences of Large Devaluations," *American Economic Review*, 107(11), 3477–3509.

DellaVigna, S., and M. Gentzkow (2019): "Uniform Pricing in U.S. Retail Chains," *The Quarterly Journal of Economics*, 134(4), 2011–2084.

Frankel, D. M., and E. D. Gould (2001): "The Retail Price of Inequality," *Journal of Urban Economics*, 49(2), 219–239.

Gibson, J., and B. Kim (2013): "Do the urban poor face higher food prices? Evidence from Vietnam," *Food Policy*, 41(C), 193–203.

Handbury, J. (2021): "Are Poor Cities Cheap for Everyone? Non-Homotheticity and the Cost of Living Across U.S. Cities," *Econometrica*, 89(6), 2679–2715.

Handbury, J., and D. E. Weinstein (2015): "Goods Prices and Availability in Cities," *Review of Economic Studies*, 82(1), 258–296.

INE (2017): "Encuesta Nacional de Gastos e Ingresos de los Hogares 2016-2017," Discussion paper, Instituto Nacional de Estadística.

——— (2023a): "Estimación de la pobreza por el método del ingreso," Discussion paper, Instituto Nacional de Estadística.

——— (2023b): "Indicadores de la distribución del ingreso," Discussion paper, Instituto Nacional de Estadística.

Jaravel, X. (2019): "The Unequal Gains from Product Innovations: Evidence from the U.S. Retail Sector," *The Quarterly Journal of Economics*, 134(2), 715–783.

——— (2021): "Inflation Inequality: Measurement, Causes, and Policy Implications," *Annual Review of Economics*, 13(1), 599–629.

Jaravel, X., and D. Lashkari (2023): "Measuring Growth in Consumer Welfare with Income-Dependent Preferences: Nonparametric Methods and Estimates for the United States*," *The Quarterly Journal of Economics*, 139(1), 477–532.

Owens, A. (2019): "Do New Neighbors Pay More for Groceries?," .

Rao, V. (2000): "Price Heterogeneity And "Real" Inequality: A Case Study Of Prices And Poverty In Rural South India," *Review of Income and Wealth*, 46(2), 201–211.

A Additional Tables

Table 8: Income Baseline Estimation. Stores in the Year 2007.

Dependent Variable:	log Deflacted Price						
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
log Income	0.0269***	0.0032***	0.0099*	0.0020***	0.0010***	0.0013***	0.0018***
	(1×10^{-5})	(1×10^{-5})	(0.0049)	(1×10^{-5})	(1×10^{-5})	(1×10^{-5})	(1×10^{-5})
Fixed-effects							
Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market		Yes		Yes	Yes	Yes	Yes
Product			Yes	Yes	Yes	Yes	Yes
Chain					Yes		
Store						Yes	Yes
Product x Store							Yes
Fit statistics							
Observations	3,561,465	3,561,465	3,561,465	3,561,465	3,561,465	3,561,465	3,561,465
R^2	0.00315	0.00478	0.94109	0.94180	0.94225	0.94263	0.94783
Within R^2	0.00033	3.05×10^{-7}	0.00076	2.16×10^{-6}	5.48×10^{-7}	8.66×10^{-7}	1.79×10^{-6}

Clustered (Category & Chain) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 9: Income Quartile Estimation. Additional Controls (Stores in 2007).

Dependent Variable:	log Deflacted Price	
Model:	(1)	(2)
Variables		
log Income	0.0001	0.0016
	(0.0012)	(0.0040)
Num. Cashiers	-7.1×10^{-5}	0.0827
	(0.0002)	(432,345.6)
Sh. Prod. at Store	-0.0133	-0.0162
	(0.0186)	(0.0194)
Num. Compet. per (1,000) Pop.	-0.0008	-0.0142
	(0.0239)	(0.0094)
First Quartile	0.0063	0.0293
	(0.0122)	(0.0534)
Fourth Quartile	-0.0243	-0.0087
	(0.0200)	(0.0422)
log Income × First Quartile	-0.0028**	-0.0052
	(0.0010)	(0.0053)
log Income × Fourth Quartile	0.0057***	0.0040
	(0.0016)	(0.0045)
Num. Cashiers × First Quartile	-0.0005	-0.0003
	(0.0006)	(0.0002)
Num. Cashiers × Fourth Quartile	-0.0001	0.0006***
	(0.0003)	(0.0001)
Sh. Prod. at Store × First Quartile	0.0263	0.0240
	(0.0199)	(0.0171)
Sh. Prod. at Store × Fourth Quartile	-0.0420***	-0.0503**
	(0.0076)	(0.0171)
Num. Compet. per (1,000) Pop. × First Quartile	0.0372**	0.0332**
	(0.0135)	(0.0148)
Num. Compet. per (1,000) Pop. × Fourth Quartile	0.0070	0.0157**
	(0.0234)	(0.0068)
Fixed-effects		
Product	Yes	Yes
Chain	Yes	
Time	Yes	Yes
Market	Yes	Yes
Store		Yes
Fit statistics		
Observations	3,561,465	3,561,465
R^2	0.94229	0.94267
Within R^2	0.00066	0.00073

Clustered (Category & Chain) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*