Assessing Long-Run Price Convergence in Retailing*

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Abstract

We asses price dispersion in retail markets and its sources over time. Using a product-detailed price database, we document a consistent divergence of prices over time in retail markets in Uruguay: price dispersion increased by 3.1% in fifteen years. Next, we analyze microeconomic and macroeconomic factors that correlate with price dispersion. We differentiate the effect in the short-run—i.e., static differences between markets—and long-run effects—if these effects increase or decrease over time. Macroeconomic factors fluctuate over time in their impact on price dispersion. Microeconomic factors, mainly competition between stores and differences in category assortments between stores, have a substantial short-run correlation and an increased effect over time. When we add interactions to the trend, our measure of price dispersion, we found that price dispersion is twice higher: 6.3%.

JEL CODES: D4, F40, L1.

Keywords: Price Dispersion, Market Segmentation, Retail Industry.

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1 Introduction

There is ample evidence of long-run price convergence within countries (Parsley and Wei (1996), O'Connell and Wei, 2002, and Yazgan and Yilmazkuday, 2011 for the US; Ceglowski, 2003 for Canada; Fan and Wei, 2006 for China; and Elberg, 2016 for Mexico). Between countries, Parsley and Wei (2001), Crucini and Shintani (2008), Cavallo, Neiman, and Rigobon, 2014, and Broda and Weinstein (2008) have found price convergence for different geographic regions, while Bergin and Glick (2007) have found mixed patterns of price dispersion. Other papers have found slow convergence in specific markets, such as the European car market (Gil-Pareja, 2003; Goldberg and Verboven, 2005; Dvir and Strasser, 2018). The long-run price convergence between countries is due mainly to reduced trade costs.[1]

Another strand of the literature has studied the dispersion of prices in retail markets (Nakamura, 2008; Kaplan and Menzio, 2015; Hitsch, Hortaçsu, and Lin, 2021). These studies provide decomposition to understand the sources of price dispersion, mainly between factors related to stores, products, and chains. Nevertheless, these papers need to analyze the evolution of price dispersion and how the different factors affect it in the long run.

In this paper, we first document an increase in price dispersion in retail markets in Uruguay over time. Following Dvir and Strasser (2018), we define price dispersion as the standard deviation of monthly prices in a geographical market, expressed as a city or neighborhood in the capital city. We regress our variable of price dispersion to controls and a trend to analyze price dispersion. Using a detailed database for a limited number of products, we found prices to divert between 3.1% and 3.3% in fifteen years. Next, following loosely the literature on macro price dispersion, we study the effect of sources that may correlate with price dispersion. We define three micro-related sources of price dispersion related to the competition between stores, the number of varieties offered, and

[1]For example, the European integration process has resulted in the removal of barriers that facilitate the convergence of prices (Goldberg and Verboven, 2005), as also does the introduction of a common currency (Glushenkova and Zachariadis, 2016; Cavallo, Neiman, and Rigobon, 2015).

the total number of varieties at the store. We also define four macro-related sources of price dispersion: unemployment, income, the dispersion of income, and population.

We relate these seven sources to price dispersion and find that micro sources are consistently associated with an increase in price dispersion in the short-run, i.e., static differences between markets. We then interact our correlated sources with the trend and find that micro sources have long-run increasing impacts on price dispersion, i.e., the static effect of these variables increases over time. Also, the trend coefficient increases when interacting with our sources of dispersion, which shows the price trend may be hidden behind other sources that affect it. Finally, we split our sample between stores within the same chain and between chains. Consistent with the literature (DellaVigna and Gentzkow (2019)), price dispersion between chains is higher than within chains. Chains respond less to macroeconomic local factors, consistent with prices being uniform within chains.

The paper contributes to two different strands of the literature. First, we contribute to the international trade literature by showing evidence of increasing price dispersion in a small and open economy. We introduce seven sources of price dispersion and evaluate their short-run—static—and long-run—dynamic—impact and their differentiated effect on the convergence of stores in retail chains. Second, we contribute to the macro literature by analyzing the long-run relative dispersion of retail prices. Previous work has decomposed price dispersion in static components but has yet to explore how they change over time. We provide evidence of how these sources—mainly competition between stores and differences in product categories—have long-run impacts on price dispersion. This implies that each factor's relative size affects the dispersion change over time.

The literature applied two methodologies to study price dispersion—as in the macro literature—or convergence to the law of one price (LOP)—as in the trade literature. One examined the half-life of prices to convergence (e.g., Elberg, 2016). At the same time, the other studies have calculated the standard deviation of prices (e.g., Dvir and Strasser, 2018), more closely related to the macro literature. We will analyze if a trend in the standard deviation of product prices exists at one point in time and geographical market. In turn, authors differ in the methodology for decomposing price dispersion and the categories affecting price dispersion. Lach (2002) filter prices by observable products and store characteristics—fixed effects—and study the residuals and characterize price dispersion. Nakamura (2008) propose a variance decomposition based on fixed effects regression for demeaned price data while decomposing price dispersion between factors idiosyncratic to stores, specific to chains, and common to all supermarkets (pp.433-4). Kaplan and Menzio (2015) decompose prices into fixed effect terms and retail, retail-store, and retail-good components (pp. 1182-3). Finally, Hitsch, Hortaçsu, and Lin (2021) proposes a variance decomposition approach between markets, stores, and within stores (pp. 309).

Previous literature has also tried to disentangle price dispersion. Related to our paper is Martín-Oliver, Salas-Fumás, and Saurina (2007), who studied the convergence of interest rates in retail banking in Spain and decomposed the variance. They estimate a fixed effect model and calculate the relative explanatory power of each effect when removed. While we made a similar study for the retail grocery market, our methodology decomposed between short-run and long-run effects, which could differ from the one used by omitting variables.[2] Also, Faber and Stokman (2009) studied the sources of price dispersion in Europe using CPI information and analyzed its determinants (tax rates, input costs, exchange rate volatility, and openness), using cointegration techniques, and Glushenkova and Zachariadis (2016) decompose price dispersion between products and countries characteristics (traded goods, non-traded inputs, differences in the value-added tax (VAT).[3] Finally, Zhao (2006) analyzes price dispersion in retail markets, with particular detail on the microeconomic sources of price dispersion. Our paper uses detailed Universal Product Code(UPC)-level information and a microeconomic-related source of price dispersion within a country. Also, it decomposes the bases of price dispersion

[2]Omitting variables could also bias the estimation of coefficients and their relative importance.

[3]See also Rumler and Reiff (2014) for a comparison of within and between countries price dispersion and its link to countries characteristics for Europe.

between short-run and long-run effects.

Our unique database of retail prices in a small country is excellent for performing the study. The database has had daily prices for nearly all supermarkets in Uruguay for almost sixteen years, one of the most prolonged retail prices databases in the literature.[4] The database contains information about a limited number of products defined at the Universal Product Code (UPC)—the three most selling brands in a category—and the store—exact location, whether it belongs to a chain, and the number of cashiers. This information allows for evaluating price dispersion and the forces driving price dispersion. For a given price, we have information on the market—location, product, category (i.e., Pilsen 1 liter beer), store chain, and the exact time the price is available.

The paper is structured as follows. Section 2 presents detailed information on the database. Section 3 shows the dispersion of prices in the database. Next, Section 4 studies the correlation of price dispersion with micro and macro sources. Next, in Section 5, we repeat the analysis for stores within or between chains. Section 6 concludes.

2 Data

We perform the analysis using a detailed product database of daily posted prices compiled by The General Directorate of Commerce (DGC, by its Spanish acronym), a branch of the Ministry of Economy and Finance in Uruguay, which comprises information about grocery stores all over the country.[5] The DGC requires retailers to report their daily prices once a month using an electronic survey.

The database originates in a tax law passed by the Uruguayan legislature in 2006, which changed the tax base and the VAT rates. The Ministry of Economy and Finance was concerned about incomplete pass-through from tax reductions to consumer prices and hence decided to collect and publish the prices in different grocery stores across the country. The DGC issued Resolution Number 061/006, which mandates that grocery

[4] The database does not have information on small groceries.

[5] This is an updated database from Borraz and Zipitría (2012) and Borraz, Cavallo, Rigobon, and Zipitría (2016).

stores report their daily prices for a list of products if they meet the following two conditions: i) they sell more than 70% of the products listed, and ii) they either have more than four grocery stores under the same brand name or have more than three cashiers in a store. The information each retailer sends is a sworn statement, and there are penalties for misreporting. The objective of the DGC is to ensure that prices posted on the DGC website reflect the actual prices published in the stores. Moreover, the DGC is responsible for enforcing the Consumer Protection Law. As a result, stores are free to set the prices they optimally choose, but they face a penalty if they try to misreport them to the DGC in an attempt to mislead customers.

The data includes daily prices from April 1, 2007, to December 31, 2022, for 154 products, the vast majority defined by the UPC. This detailed information allows us to track the same good in stores nationwide, avoiding measurement problems from comparing different products (see the discussion in Atkin and Donaldson, 2015). The markets included in the sample represent 15.6% of the Uruguayan Consumer Price Index (CPI) basket. Most items have been homogenized to make them comparable, and each store must always report the same item. For example, all stores report the carbonated soft drinks of the international brand Coca-Cola in its 1.5-liter variety. No price is reported if this specific variety is unavailable at a store. The data is then posted on a website that allows consumers to check prices in different stores or cities and to compute the cost of different baskets of goods across locations.[6]

The three best-selling brands are reported for each market, disregarding the store's brands. Exceptions are sugar, crackers, and cocoa, which has only two brands, and rice, which has up to six brands. Products were selected after a survey of the largest store chains in 2006. In November 2011, the list of products was updated, including some markets and reviewing the top-selling brands for others. The price information for the goods that were discarded was deleted from the database, and the price information was lost in some

[6]See https://www.precios.uy/objetivos/ and https://www.precios.uy/sipc2Web/ for the objectives and data. See also Borraz and Zipitría (2012) for a detailed description of the database and an analysis of price stickiness.

markets. The 154 products in the database represent more than 60 markets defined at the product category level (e.g., sunflower oil, corn oil, wheat flour 000, and wheat flour 0000 are different markets in our analysis). For some of them, the information does not allow the identification of the goods at the UPC level; in the meat and bread markets, products do not have brands. The detailed list of goods can be found in Appendix B.

For each store, we have detailed information about the exact location given by its Universal Transverse Mercator (UTM), whether it belongs to a chain, and the number of cashiers. The database has information for up to 539 stores—i.e., a non-balanced panel—across all nineteen Uruguayan political states, comprising 54 cities. Montevideo is Uruguay's capital city and also the country's largest city, with nearly forty percent of the Uruguayan population and 54% of all stores in the sample.[7] In the analysis, we define each city as a market, except for Montevideo, where we define a neighborhood as a market.

We identified 125 products out of 154 that could be precisely matched. We delete products that are sold unpackaged (e.g., ham, meat, and poultry). Our final database has 125 products corresponding to 42 categories. We also delete information on drugstores, as there is partial information on goods for these stores. For the selected goods, the database has nearly 155 million daily observations. We delete outliers as those prices higher than three times or less than one-third of the median monthly price for each product (less than 0.01%). We then calculate the mode monthly price for each product to study price dispersion that is not due to sales. The mode price is used in the analysis because Nakamura, Nakamura, and Nakamura (2011) found for the US that most of the price dispersion is explained by sales, while Eichenbaum, Jaimovich, and Rebelo (2011) showed that reference prices tend to display inertia compared to nominal prices. In addition, we used monthly data because our database has fifteen years, and Sheremirov (2020) showed that inflation co-moved with price dispersion for regular prices. Still, that relation is negative if there are sales in the data. Finally, we deflated prices by CPI as monthly

[7]More information is available at http://www.ine.gub.uy/uruguay-en-cifras.

average inflation was 0.65%, and prices tripled in the period. The mode-deflated price avoids inflation-induced movements in price dispersion. Our final database is composed of 4,940,552 observations. Table 1 below shows the database's descriptive statistics and the variables used in the analysis.

Table 1: Summary Statistics.

	Stores			ECH	
	Mean	St. D		Mean	St. D
CPI Adjusted Log Price	3.272	0.545	Unemployment Rate	0.076	0.034
St. D. Adjusted Log Price	0.056	0.064	Log Population	10.457	1.579
Category Entropy	0.272	0.334	Log Av. CPI Adjusted Income▲	9.504	0.403
St. D. of Share of Product in Stores	0.048	0.051	St. D. of Adjusted Income	9.154	0.467
Number of Competing Stores*	2.747	3.736			
Sample Period	04/2007	12/2022		04/2007	06/2022
Number of Observations	4,940,552			-	
Number of Stores	539			-	
Number of Chains	23			-	
Number of Markets (location)	118			70	
Number of Products	125			-	
Number of Categories	42			-	

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

3 Convergence

We measure price dispersion with the standard deviation of log Consumer Price Index (CPI) adjusted prices (Dvir and Strasser, 2018). The equation for estimating price dispersion across time is:

$$SD_{it}^{m} = \alpha + \alpha_i + \alpha_{mo} + \alpha^m + \beta \tilde{p}_{it}^{m} + \gamma t + \epsilon_{it}^{m}, \quad (1)$$

where SD_{it}^{m} is the standard deviation—in percentage—of the log CPI adjusted price of product i in time t and market m, $\tilde{p}_{it}^m$ is the average log CPI adjusted price of product i in time t and market m, t is a linear trend, α_i are product-dummies, α_{mo} are month-dummies, α^m are market-dummies, and ϵ_{it}^m is an error term. Table 2 below shows the estimation of Equation 1 by weighted least squares using the number of stores as weights and with standard errors clustered at the product-time level.

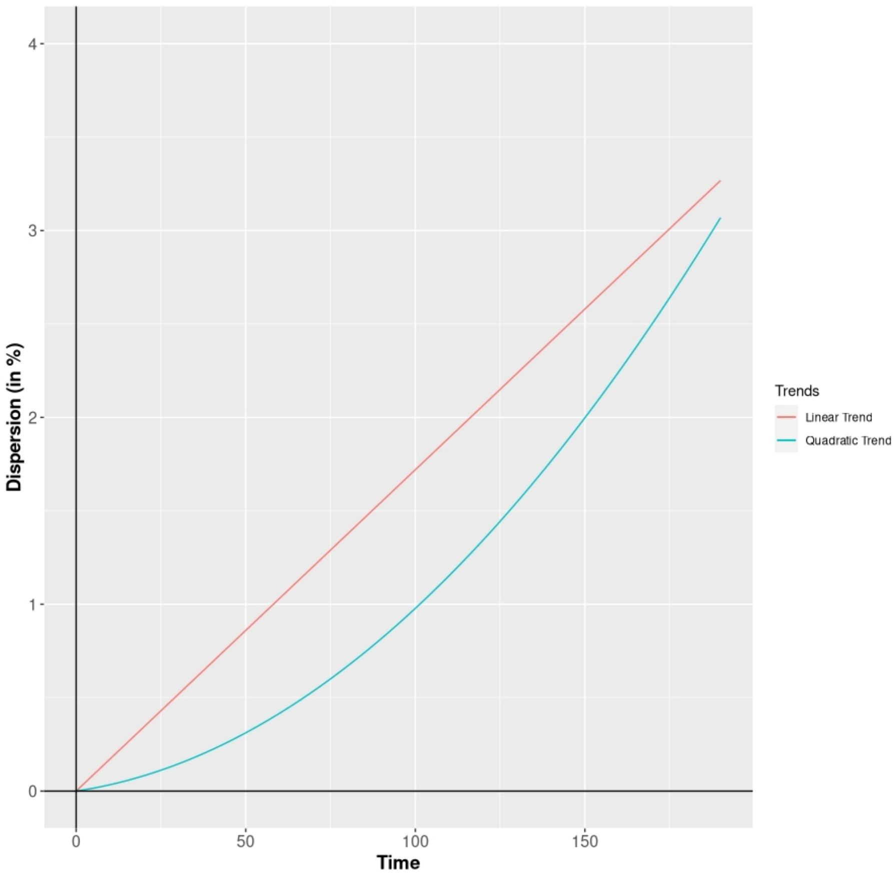
Table 2: Convergence Baseline Estimation.

Dependent Variable:	SD (in %)				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Constant	11.14***				
	(0.1517)				
Av. Price	-2.121***	-7.503***	-2.024***	-6.796***	-6.785***
	(0.0461)	(0.2006)	(0.0458)	(0.2005)	(0.2007)
Time	0.0179***	0.0160***	0.0192***	0.0172***	0.0027*
	(0.0005)	(0.0004)	(0.0005)	(0.0004)	(0.0014)
Time^2					7.08×10^{-5}***
					(7.54×10^{-6})
Fixed-effects					
Product		Yes		Yes	Yes
Month		Yes	Yes	Yes	Yes
Market			Yes	Yes	Yes
Fit statistics					
Observations	1,008,944	1,008,944	1,008,944	1,008,944	1,008,944
R^2	0.05619	0.16616	0.12111	0.22415	0.22491
Within R^2		0.04768	0.05964	0.04832	0.04925

Clustered (Product-Time) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

All five columns in Table 2 show no convergence of prices in the sample. Adding product-dummy controls—Column (2)—market-dummy controls—Column (3)—or both—Column (4)—does not change the coefficient substantially. Lastly, as in Dvir and Strasser (2018), we add a quadratic trend to check for the non-linearity of price dispersion and find that the dispersion also increases over time. Figure 1 below shows the linear and quadratic trends estimated in Columns (4) and (5) of Table 2. Nevertheless, the total increase in dispersion is large: 3.3% for the linear trend and 3.1% for the quadratic term.

Figure 1: Price Dispersion in Time.



As convergence conditions can shift over time, we split the sample in two: until and above the median time, which is June 2015. We estimate Equation 1 for the linear and quadratic trend for the two sub-samples. Table 3 below shows that the dispersion of prices increases in both periods, but the increase is higher in the second period.

Figure 2 below shows the linear and quadratic trends estimated in Table 3 for the split sample. The figure made clear that the increase in price dispersion is more pronounced in the second period of the sample.

The previous analysis was done with all stores in the sample. As the database is an unbalanced panel, price dispersion may reflect that new stores have different prices than existing ones. To check this result, we re-estimate Equation 1 only for the active stores in 2007, with complete dummies, linear and quadratic trends, and until and above the median time. The following Table shows that price divergence is not due to introducing

Table 3: Convergence Baseline Estimation. Before and After Median Time

Dependent Variable:	SD (in %)			
Model:	Until June 2015		After June 2015	
Model:	(1)	(2)	(3)	(4)
Variables				
Av. Price	-3.636***	-3.575***	-10.24***	-11.01***
	(0.2074)	(0.2088)	(0.3621)	(0.3795)
Time	0.0095***	-0.0063**	0.0165***	-0.0493***
	(0.0006)	(0.0026)	(0.0014)	(0.0056)
Time^2		0.0001***		0.0008***
		(2.23×10^{-5})		(6.56×10^{-5})
Fixed-effects				
Product	Yes	Yes	Yes	Yes
Market	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Fit statistics				
Observations	537,777	537,777	471,167	471,167
R^2	0.22932	0.22983	0.26236	0.26495
Within R^2	0.00997	0.01064	0.04181	0.04518

Clustered (Product-Time) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

new stores in the sample.

First, comparing Column (4) of Table 2 and Column (1) of Table 4, we found that although the trend coefficient is 30% smaller, it remains statistically significant. Also, the quadratic trend is positive and statistically significant in Column (2) of Table 4, while the linear trend has a negative sign. Until median time—June 2015—coefficients are much smaller but remain statistically significant and in line with those of Columns (1) and (2) of Table 3. After the median time, all coefficients are similar to those in Columns (3) and (4) of Table 3. Figure 3 below plots the price dispersion for stores in 2007, which is similar to Figures 1 and 2. In conclusion, Tables 2, 3, and 4 show that the increase in price dispersion is a general phenomenon concentrated mainly in the second period of the sample.

As dispersion estimations between the entire database and the original store's database

Figure 2: Price Dispersion in Time.

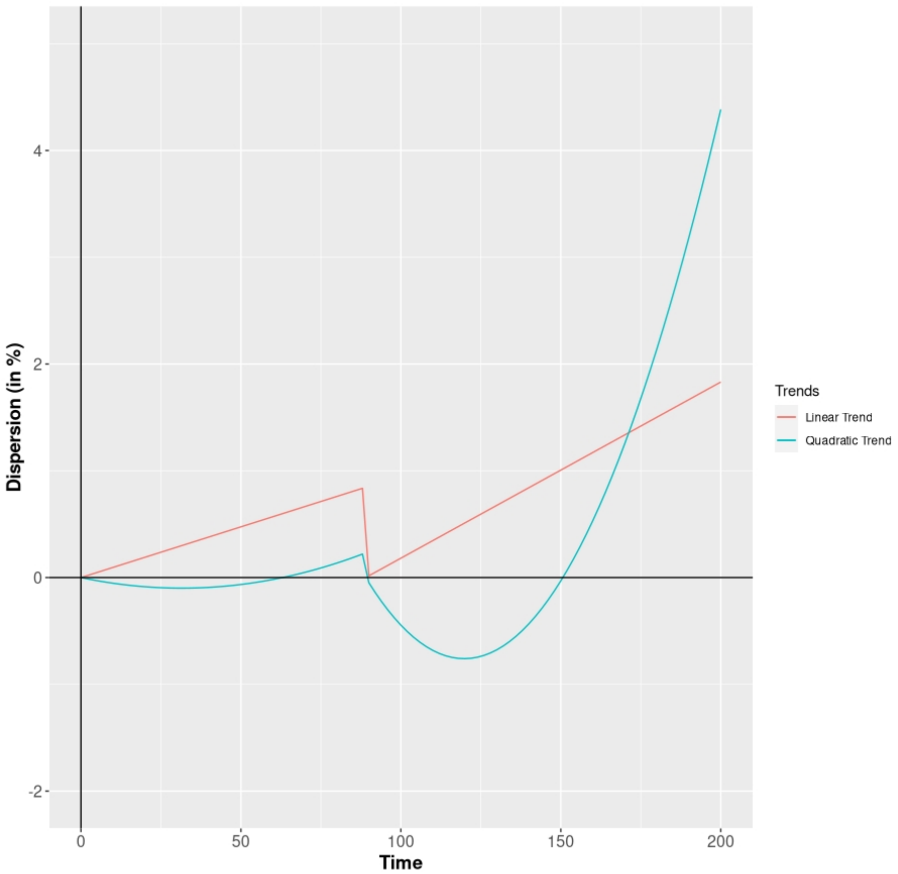
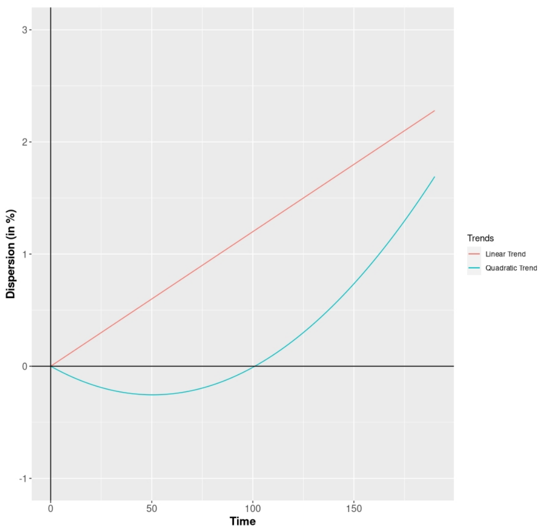
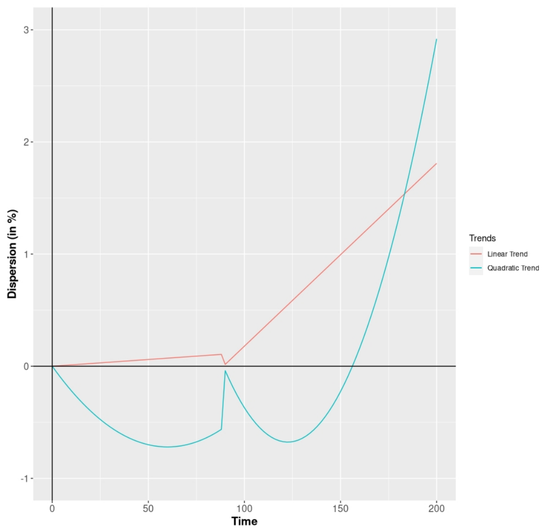


Figure 3: Price Dispersion in Time: Stores in 2007.



(a) Full Sample.



(b) Until and Before June 2015.

do not differ, we will analyze using the whole database. Also, to make the coefficient interpretation more accessible, we will include only a linear trend in the estimations

Table 4: Convergence Baseline Estimation. Stores in the year 2007.

Dependent Variable:	SD (in %)					
Model:	Full Sample		Until June 2015		After June 2015	
Variables						
Av. Price	-6.331***	-6.240***	-2.530***	-2.415***	-10.59***	-11.27***
	(0.1944)	(0.1939)	(0.1914)	(0.1917)	(0.3603)	(0.3763)
Time	0.0120***	-0.0101***	0.0012*	-0.0240***	0.0163***	-0.0403***
	(0.0004)	(0.0014)	(0.0006)	(0.0027)	(0.0012)	(0.0047)
Time^2		0.0001***		0.0002***		0.0006***
		(7.19×10^{-6})		(2.48×10^{-5})		(5.22×10^{-5})
Fixed-effects						
Product	Yes	Yes	Yes	Yes	Yes	Yes
Market	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	793,113	793,113	412,728	412,728	380,385	380,385
R^2	0.21999	0.22220	0.25342	0.25488	0.24916	0.25166
Within R^2	0.03594	0.03866	0.00400	0.00595	0.04769	0.05087

Clustered (Product-Time) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

below. Although some non-linearities may exist in the data, the interpretation became more complex with multiple coefficients, as explored below.

4 Source of Dispersion

What are the sources, or to which variables correlate, price dispersion over time? We analyze three micro sources and four macro sources of price dispersion. Micro sources will typically be endogenous to price dispersion, so they should be both present: price dispersion and micro sources. We explore three micro sources: store assortment differences in categories, the total number of products each store offers, and differences in competition between stores. In Borraz and Zipitría (2022), we show that if two stores differ in the products offered in a given product category, the convergence of prices for the common product is less likely (also see Cavallo, Feenstra, and Inklaar (2023)). The diversity of products in a category between stores shows the diversity in the competition between products in a given category. A product category is defined as usually defined in the literature (Nakamura, 2008), i.e., beer. This analysis emphasizes the role of competition between products rather than between stores (Kaplan, Menzio, Rudanko, and Trachter, 2019). Our database has a limited number of products for each category (e.g., beer), so we create an entropy index to measure the relative similarity of products offered by stores in a given category in a market and time. The (general) entropy index is calculated as $E_t^{m,c} = -\frac{N_i}{\sum_{i \in c} N_i} \ln\left(\frac{N_i}{\sum_{i \in c} N_i}\right)$, and higher numbers implied more diverse assortments of stores. According to Table 1, the mean $E_{it}^{m,c}$ in the database is 0.272, and the standard deviation is 0.545.

In Borraz, Carozzi, González-Pampillón, and Zipitría (forthcoming), we estimate the impact of the differences in the number of products the store offers on prices and found that stores can increase the number of the products provided to deter entry into the market. So, we include the variation within markets in the number of products as a source of price dispersion. In particular, we measure the difference in the total number of products between stores by calculating the standard deviation of the share of products each store has over the number of products available each time: $SDP_t^m = sd_t^m \left(\frac{\#products_{jt}^m}{\#product_j}\right)$. The mean of SDP_t^m is 0.048, and the standard deviation is 0.051. Finally, differences in competition within a market have been proposed by Berardi, Sevestre, and Thébault (2017), so we create a variable $N_t^m = \sum_{j \in J_t^m} \mathbf{1} - 1$, that count the number of stores for each time t and market m less one. The mean number of competitors in the database is 2.75, and the standard deviation is 3.74.

Macro sources of price dispersion are usual in the literature. We include unemployment as the share of unemployed over the sum of employed and unemployed for a three-month window in each neighborhood for Montevideo, or department (UR_t^m), to measure cyclical shocks to the markets. Secondly, there is the size of the market (Berardi, Sevestre, and Thébault (2017)) measured by population (Pop_t^m) and calculated as the log sum of employed and unemployed for a three-month window in each neighborhood for Montevideo or department. Next, we include income (Berardi, Sevestre, and Thébault

(2017)) measured as the log of income for a three-month window in each neighborhood for Montevideo, or department (Inc_t^m), and captures the relative wealth of the market. Finally, we include income dispersion (Zhao (2006)) measured as the standard deviation of income for a three-month window in each neighborhood for Montevideo, or department ($SDInc_t^m$) that captures the heterogeneity of the income distribution in the market.

We want to analyze the short-run sources of price dispersion, measured by the micro and macro variables. But we also want to know how those variables affect the long-run price dispersion. That is how they co-evolve in time. Do the variables have long-run effects on price dispersion? If yes, how much of the trend is correlated with each variable?

Next, we add our seven variables to Equation 1 in Equation 2:

$$\begin{aligned} SD_{it}^m = \alpha + \alpha_i + \alpha_{mo} + \alpha^m + \beta \tilde{p}_{it}^m + \underbrace{\eta_1 E_t^{m,c} + \eta_2 N_t^m + \eta_3 SDP_t^m}_{micro\,sources} \\ + \underbrace{\theta_1 UR_t^m + \theta_2 Pop_t^m + \theta_3 Inc_t^m + \theta_4 SDInc_t^m}_{macro\,sources} + \gamma \times t + \epsilon_{it}^m, \end{aligned} \tag{2}$$

where subindexes are i for product, t for time, and mo for month; and superindexes are m for market and c for category.

Table 5 below shows the estimations of Equation 2 including all dummies, using the number of stores as weights, and with standard errors clustered at the product-time level. As the previous section has shown differences in time among different periods, we estimate Equation 2 for the entire database until and after the median period.

First, we point out that different forces at work correlate with price dispersion. The trend is positive and statistically significant for the whole database and the first period of the sample but not for the second period. This result is interesting as we previously showed that the trend is ample for the second period (see Table 3. Secondly, entropy and competition positively correlate with price dispersion: more competition and differences between producers in the product varieties offered increase price dispersion. The differences in the number of products stores offer positively affect the entire database. However, the

Table 5: Sources of Price Convergence: Short-run.

Dependent Variable:		SD (in %)	
Model:	Full Database	Until June 2015	After June 2015
Variables			
Av. Price	-7.235***	-3.659***	-13.59***
	(0.2105)	(0.2080)	(0.5037)
Time	0.0126***	0.0065***	-0.0023
	(0.0004)	(0.0007)	(0.0022)
Cat. Entropy	0.4914***	0.2975***	0.7604***
	(0.0404)	(0.0351)	(0.0721)
Num. Comp. Stores	0.1598***	0.1865***	0.1693***
	(0.0102)	(0.0087)	(0.0143)
SD Sh. Prod.	0.0104***	0.0153***	-0.0486***
	(0.0023)	(0.0028)	(0.0041)
Log Pop.	0.0072	-0.0035	-0.1501***
	(0.0098)	(0.0077)	(0.0532)
Unemp. Rate	2.449***	3.447***	0.0180
	(0.3047)	(0.3445)	(0.4528)
Log Income	0.0160	0.3796***	-0.7448***
	(0.1286)	(0.1020)	(0.2399)
SD Income	1.22×10^{-6}	3.06×10^{-6}**	-1.39×10^{-5}***
	(1.3×10^{-6})	(1.22×10^{-6})	(2.89×10^{-6})
Fixed-effects			
Product	Yes	Yes	Yes
Market	Yes	Yes	Yes
Month	Yes	Yes	Yes
Fit statistics			
Observations	900,117	537,097	363,020
R^2	0.22705	0.23224	0.28264
Within R^2	0.04699	0.01360	0.05600

Clustered (Product-Time) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

sign changes when the sample is split: for the first period, it is correlated positively with price dispersion and negatively in the second period. On the macro sources, income and the dispersion of income are not statistically significant for the whole database, but this is explained by the change of signs between periods. The unemployment rate is positive for the entire database and the first period but is insignificant in the second one. Lastly, the market size seems to correlate—negatively—with dispersion only in the second period. While some factors consistently relate to price dispersion—competition, varieties— other factors are at play at different times, and their impact differs.

If we consider the entire database, one standard deviation of variety differences explains nearly 30% of the standard deviation of price dispersion,[8] while one standard deviation in competition explains more than one standard deviation of price dispersion.[9] Among the macro factors, one standard deviation in the unemployment rate (0.034) explains only 15% of the standard deviation of price dispersion. In the aggregate, competition between stores is the main driving force that correlates with differences in price dispersion between markets.

Next, we analyze the long-run effects of those variables on price dispersion. The previous analysis shows static differences in price dispersion between markets. However, the effect of each variable varies in time, as the split sample shows. We now interact the seven sources of price dispersion with the trend to know which one has a lasting co-movement. Call now Call $X = E_t^{m,c} + N_t^m + SDP_t^m$ and $Y = UR_t^m + Pop_t^m + Inc_t^m + SDInc_t^m$ and now Equation 2 became:

$$\begin{aligned} SD_{it}^m = \alpha + \alpha_i + \alpha_{mo} + \alpha^m + \beta \tilde{p}_{it}^m + \eta_1 X + \theta_1 Y \\ + \eta_2 X \times t + \theta_2 Y \times t + \gamma \times t + \epsilon_{it}^m, \end{aligned} \tag{3}$$

where subindexes are i for product, t for time, and mo for month; and superindexes are m for market and c for category.

We estimate Equation 3 with a complete set of dummies, using the number of stores as weights, and with standard errors clustered at the product-time level. The results are shown in the Table 6 below. Due to the large number of coefficients, we report only the trend and its interactions.

[8]From Table 1 the standard deviation of entropy is 0.334, while the estimated coefficient is 0.4914, which results in 0.164 or 30% of 0.545 which is the standard deviation of the dispersion in prices.

[9]The standard deviation of competition is 3.736, and the estimated coefficient is 0.1598. This results in 0.597, which is 110% of the standard deviation of price dispersion.

Table 6: Sources of Price Convergence: Long-run effects.

Dependent Variable:	SD (in %)
Model:	Full database
Variables	
Time	0.0329***
	(0.0094)
Time × Cat. Entropy	0.0101***
	(0.0009)
Time × Num. Comp. Stores	0.0005***
	(4.37×10^{-5})
Time × SD Sh. Prod.	-3.52×10^{-5}
	(5.1×10^{-5})
Time × Log Pop.	-0.0017***
	(0.0002)
Time × Unemp. Rate	-0.0549***
	(0.0068)
Time × Log Income	0.0003
	(0.0009)
Time × SD Income	$-5.28 \times 10^{-7***}$
	(3.29×10^{-8})
Fixed-effects	
Product	Yes
Market	Yes
Month	Yes
Fit statistics	
Observations	900,117
R^2	0.22868
Within R^2	0.04899

Clustered (Product-Time) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Firstly, the Table shows that price dispersion results from complex and conflicting effects. Some variables have an enduring positive effect on dispersion, while others fade away or even reverse. This is also reflected in the estimation of the time trend that nearly duplicates in value—0.0329 versus 0.0172 in Column (4) of 2. This result shows that the sources identified have changed over time, and the—unexplained—trend in price dispersion seems biased due to these contradictory effects. The increase in price dispersion when using the new estimate is a large 6.3%.

Secondly, in terms of the effect on long-run rice dispersion, entropy and competition have a positive long-run impact on price dispersion that accumulates in time. This correlates with the consistent positive short-run effects in Table 5. On the other hand, differences in the number of products handled by stores, unemployment, and the market's income dispersion all affect the decline in time. This explains why the coefficient reverses in Columns (2) and (3) of Table 5 or, in the case of unemployment, the effect disappears in time. On the other hand, income has only short-run effects, but its impact on price dispersion is ambiguous.

Lastly, while most coefficients seem small compared with the trend, the positive effect of entropy is worth highlighting. The coefficient is nearly one-third of that of the trend and nearly 60% the size of the original estimated trend in Column (4) of Table 2. Compare this with the competition coefficient, which is two orders of magnitude lower. Also, it explains how the short-run effect nearly triples between the first and second periods in Table 5. While competition has a short-run robust impact, differences in categories have a much stronger long-run effect on price dispersion. Having stores that consistently differ in the options offered within a product category is associated with the same product pricing path towards heavily diverging in time.

5 Chains

Of all the six possible sources of variation that can explain price dispersion in our data—store, product, category, market, time, and chain—our analysis of dispersion at the product level allows only five components, as store-specific product dispersion cannot be studied. Previously, we analyzed seven of the sources of price dispersion. Nevertheless, Nakamura, Nakamura, and Nakamura (2011) and DellaVigna and Gentzkow (2019) have shown that stores with the same chain have very different pricing behavior than independent stores. In particular, stores within the same chain tend to have similar prices; i.e., dispersion within chains should be lower than between chains.

Our previous analysis has both the effect of within and between chains in price dispersion. Our database has two store types: independent stores and chain stores. We create two new databases to check differences in price convergence within and between chains. First, we pick only those stores with a chain; i.e., we drop all independent stores. Then, we create a within-chain database by recalculating all the variables at the chain and market level, so SD_{it}^{m} is now $SD_{it}^{m,s}$. All other micro variables will be calculated for each time, market, and chain (product or category if defined). Finally, we split our variable of competing number of stores in two: $NComp_t^m = \sum_{j \in J_t^m, j \notin S} \mathbf{1} - 1$, which measures the number of stores for each time-market that does not belong to chain S, and $NCh_t^m = \sum_{j \in J_t^m, j \in S} \mathbf{1} - 1$, which are the number of stores that belong to the same chain S.

Second, we create a between-chain database by picking the median chain price, median chain varieties, and median chain share of products for each chain and market. Next, we keep just one store per chain per market, i.e., the median chain store. We calculate all micro variables defined in Section 4 for each database: the chain-market database for chains and the between-chains database, after eliminating duplicated chain stores in a market.

5.1 Convergence: Chains

Before analyzing the relative convergence of prices in chains, it should be noted that prices' dispersion is quite different than between chains. Table 1 shows that the mean deviation of prices in the database is 0.056 with a standard deviation of 0.065. The mean price deviation within chains is 0.01, less than a sixth of the median price deviation between chains of 0.066. The standard deviation of price dispersion is 0.03 within chains and 0.069 between chains. Although differences do not seem as large as the median, it should be noted that the medians are pretty different; the following analysis will pick very subtle differences within chains more easily than between chains. So, while results may look statistically significant and the coefficient large within chains, their magnitude for comparison is quite different than between chains.

We estimate Equation 1 for each database, calculating a linear and a quadratic trend and then splitting the sample below and after the median period. We include a complete set of dummies—including chain-market dummies for the within-chain database—and weight by the total number of stores for the between-chain database or by the number of stores associated with the chain in the market in the within-stores database. Standard errors are clustered at the product-time level. Table 7 below shows the within and between chains estimations for the linear, and linear and quadratic trends. In 10 in Appendix A, we offer the figures until and after the median period.

Table 7: Price Convergence: Within and Between Chains.

Dependent Variable:	SD (in %)			
Model:	Within Chains		Between Chains	
Variables				
Av. Price	-1.751***	-1.728***	-9.653***	-9.665***
	(0.0785)	(0.0779)	(0.2471)	(0.2469)
Time	0.0005***	-0.0061***	0.0223***	0.0035**
	(0.0002)	(0.0006)	(0.0004)	(0.0017)
Time^2		3.29×10^{-5}***		9.19×10^{-5}***
		(3.11×10^{-6})		(8.65×10^{-6})
Fixed-effects				
Product	Yes	Yes	Yes	Yes
Market-chain	Yes	Yes		
Month	Yes	Yes	Yes	Yes
Market			Yes	Yes
Fit statistics				
Observations	747,716	747,716	884,952	884,952
R^2	0.13409	0.13468	0.24062	0.24168
Within R^2	0.00648	0.00717	0.06912	0.07041

Clustered (Product-Time) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 7 shows very different convergence patterns within and between chains. While there seems to be dispersion within chains, the monthly price dispersion is about 2% of the monthly price dispersion between chains (i.e., 0.0005 versus 0.0223). Also, as noted before, the median price dispersion within chains is much smaller than between chains, so while the coefficient is statistically significant, it picks tiny differences between stores within a chain. As an example, after 100 periods the median price one standard deviation of the dispersion of prices will add 0.000015 to price dispersion—0.0005(coefficient) $\times$ 100 (periods) $\times$ 0.03 (standard deviation) $\times$ 0.01 (mean price dispersion)—within chains and 0.01 between chains—0.0228 $\times$ 100 $\times$ 0.069 $\times$ 0.066—that is 0.1% of differences in prices. The linear and quadratic terms between firms are positive, while the sign is ambiguous within firms. Furthermore, Table 10 in Annex A shows that chains show price convergence within their stores until the median period. At the same time, there is a sharp increase in dispersion between chains. After the median period, prices within chains seem to begin diverging—although not clearly—but between stores, the pattern of price dispersion continues. Price divergences are consistently a between-chains phenomena.

5.2 Source of Dispersion: Chains

We now apply Equations 2 and 3 to both databases to understand which variables correlate with price dispersion within and between chains. If patterns of price dispersion differ, then the same variable should have a different impact on prices within and between chains. The following Table shows the results for 2 for both within and between chains.

The sources of price dispersion are different within and between chains. Coefficients in this section should be interpreted as how variables correlate rather than for their value, as dispersion within and between chains is very different. First, it should be noted that the trend for stores within chains is insignificant when sources are considered. On the contrary, the trend between chains remains significant and nearly unchanged in value. Second, except for population, prices within chains do not respond to the particular macroeconomic environment of the market. This result is consistent with DellaVigna and Gentzkow (2019), who showed that stores within chains tend to charge uniform prices and should respond less to the market environment. The negative sign coefficient of the size of the market—population—in the within-chains regression may account for the fact that chains may have more stores in larger markets. Then, compared to smaller markets and after controlling for other variables, chains may have less price dispersion.

Table 8: Sources of Price Convergence: Short-run. Within and Between Chains.

Dependent Variable:	SD (in %)	
Chains:	Within	Between
Variables		
Av. Price	-1.776***	-9.532***
	(0.0811)	(0.2608)
Time	0.0003*	0.0207***
	(0.0002)	(0.0006)
Cat. Entropy	0.4104***	0.2713***
	(0.0458)	(0.0427)
Num. Comp. Stores	0.0020	0.0669***
	(0.0030)	(0.0100)
Num. Chain Own Stores	0.3985***	
	(0.0128)	
SD Sh. Prod.	-0.0238***	-0.0019
	(0.0020)	(0.0026)
Log Pop.	-0.0246***	0.0071
	(0.0059)	(0.0106)
Unemp. Rate	-0.1574	3.860***
	(0.1954)	(0.3288)
Log Income	-0.0271	-0.8209***
	(0.0601)	(0.1505)
SD Income	-3.7×10^{-7}	$5.7 \times 10^{-6***}$
	(4.88×10^{-7})	(1.6×10^{-6})
Fixed-effects		
Product	Yes	Yes
Market-chain	Yes	
Month	Yes	Yes
Market		Yes
Fit statistics		
Observations	654,716	789,026
R^2	0.14394	0.23775
Within R^2	0.00912	0.06334

Clustered (Product-Time) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note that the coefficient of the market size is insignificant between chains, reinforcing the previous result. When comparing dispersion between chains, stores respond unequally to unemployment by rising price dispersion. Also, stores in different chains react to a more unequal market—greater standard deviation of income—by differentiating their prices. Also, differences in income between markets do not increase price dispersion but decrease it. This coefficient, and the previous result about inequality in the market, could be interpreted as a store's pricing responding more strongly to inequality within the market than to imbalance between markets.

Microsource results also show differences within and between chains. First, stores within the same chain respond more strongly to stores of the same chain in the market than to competitor stores, contrary to stores in different or no chains. Differences in the number of products reduce price dispersion within and between chains. However, the more interesting result is that stores within a given chain respond more strongly—coefficient 1.5 times larger—to differences in the number of product varieties than between chains. In Table 11 in Appendix A, we present the estimation of Equation 2 within and between chains until and after the median period. As before, different periods show different correlations with the variables. Within chains, more variables seem to be associated with price dispersion but with changing effects in time. Between chains, micro factors seem more consistent than macro ones in explaining price dispersion, particularly in increasing it. More interestingly, the trend within chains is negative in the first period and positive in the second one, while positive in the first period between chains and insignificant in the second. These sharp differences show that price dispersion does not follow a linear additive path. By slicing the database, we can miss the bigger picture of prices.

Finally, Table 9 below shows how sources correlate in the long run with price dispersion. The trend heavily increases within chains and duplicates between them, indicating that the underlying forces driving price dispersion could be larger than our original estimation in Table 7. While the time trend within chains has increased two orders of magnitude, its economic effect will be small as the average price dispersion is also tiny. All macro sources are statistically negative significantly in both specifications, which points to shocks counteracting the trend in time. On the contrary, all microsources—but for the store number of products—correlate with an increase in price dispersion, even with a larger trend.

The increase in price dispersion is a puzzle: why does the trend—the unexplained

Table 9: Sources of Price Convergence: Long-run. Within and Between Chains.

Dependent Variable:	SD (in %)	
Model:	Within Chains	Between Chains
Variables		
Time	0.0283***	0.0677***
	(0.0055)	(0.0105)
Time × Cat. Entropy	0.0049***	0.0075***
	(0.0011)	(0.0010)
Time × Num. Comp. Stores	0.0002***	0.0009***
	(2.32×10^{-5})	(9.11×10^{-5})
Time × Num. Chain Own Stores	0.0025***	
	(5.64×10^{-5})	
Time × SD Sh. Prod.	-0.0006***	0.0001**
	(5.27×10^{-5})	(5.75×10^{-5})
Time × Log Pop.	-0.0024***	-0.0022***
	(0.0002)	(0.0002)
Time × Unemp. Rate	0.0013	-0.0647***
	(0.0039)	(0.0071)
Time × Log Income	-0.0009*	-0.0022**
	(0.0005)	(0.0010)
Time × SD Income	-8.46×10^{-8}***	-4.24×10^{-7}***
	(1.45×10^{-8})	(3.74×10^{-8})
Fixed-effects		
Product	Yes	Yes
Market-chain	Yes	
Month	Yes	Yes
Market		Yes
Fit statistics		
Observations	654,716	789,026
R^2	0.14988	0.23908
Within R^2	0.01600	0.06497

Clustered (Product-Time) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

tendency of prices to diverge—increase when controlled by other factors? We offer two possible answers. First, price dispersion seems affected by—correlated with—several factors. Not controlling for those factors hides the tendency of prices to diverge and biases the trend. In other words, the factors that correlate with price dispersion should have their tendency. As a result, noise is passed to the price trend and biases the actual effect. Second, as the trends for some sources are positive while others are negative, the trend effect estimated became more noisy and difficult to calculate. Take the trend estimation within chains of 7 of 0.0005. In Table 11 in Appendix A, we estimate the time trend within chains to be -0.0028 in the first period and 0.0115 in the second one. The "average" estimation for the whole sample approaches zero. So, when price dispersion is affected or correlated with other variables, its effects will be difficult to disentangle.

6 Conclusion

We analyze price dispersion in retail markets using a rich, detailed, and unique large-period database for a small open economy. Contrary to previous literature, we found retail prices to diverge between 3.1% and 3.3% in the long run. Nevertheless, this non-converge pattern changes in the period. Then, we aim to identify sources that may correlate with price dispersion, differentiated between macro and micro sources of price dispersion. Store competition and category differences relate to price dispersion, with store competition strongly associated. Macro sources have mixed short-run correlations with price dispersion, but the unemployment rate seems to increase. We next turn to the analysis of long-run price dispersion, i.e., how those sources correlate in time with dispersion. We found an increase in price dispersion when the interactions with the sources were added to the estimation equation. Also, most macro sources do not have a long-run impact, while differences in categories have the largest positive effect on price dispersion in the long run.

Next, we turn to chains. We split our database to analyze differences in price dispersion within or between chains. Within chains, price dispersion is much smaller than between chains. Divergence is a between-chains phenomenon. Chains do not respond to their environment, consistent with uniform price-setting. Store competition and category differences are correlated with price differences between stores. Between chains, macro sources have a decreasing long-run effect on dispersion, while store competition and category differences have an increasing one. Within chains, there is an increasing effect of own-store chains on long-run price dispersion.

Our analysis highlights four themes for the study of price dispersion. First, price convergence changes over time and even fluctuates. Second, sources that correlate with price dispersion might have different effects over time, even contradictory. Third, micro sources strongly correlate with price dispersion, either between or within chains. They also have a large impact over time. Fourth, the long-run dispersion of prices is very noisy, and controlling for other factors may show its true magnitude. While this analysis is exploratory, it shows that price dispersion is a complex and changing phenomenon.

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A Additional Tables

Table 10: Price Convergence: Within and Between Chains, Until and After Median Period.

Dependent Variable:	SD (in %)							
Chains:	Within				Between			
Period:	Until June 2015		After June 2015		Until June 2015		After June 2015	
Variables								
Av. Price	-1.106***	-1.121***	-2.335***	-2.262***	-4.091***	-4.006***	-15.70***	-16.70***
	(0.1107)	(0.1097)	(0.1244)	(0.1294)	(0.2284)	(0.2180)	(0.5060)	(0.5285)
Time	-0.0014***	0.0032**	0.0087***	0.0164***	0.0105***	-0.0164***	0.0189***	-0.2396***
	(0.0003)	(0.0014)	(0.0004)	(0.0016)	(0.0007)	(0.0027)	(0.0016)	(0.0229)
$Time^2$		-4.02×10^{-5}***		-9.28×10^{-5}***		0.0002***		0.0009***
		(1.24×10^{-5})		(2.05×10^{-5})		(2.38×10^{-5})		(7.77×10^{-5})
Fixed-effects								
Product	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market-chain	Yes	Yes	Yes	Yes				
Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market					Yes	Yes	Yes	Yes
Fit statistics								
Observations	371,019	371,019	376,697	376,697	479,129	473,779	405,823	405,823
R^2	0.20780	0.20793	0.15514	0.15530	0.21656	0.21924	0.28827	0.29097
Within R^2	0.00234	0.00250	0.01433	0.01451	0.01057	0.01198	0.06580	0.06934

Clustered (Product-Time) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 11: Sources of Price Convergence: Short-run. Within and Between Chains, Until and After Median Period.

Dependent Variable:	SD (in %)			
Chains:	Within		Between	
Period:	Until June 2015	After June 2015	Until June 2015	After June 2015
Variables				
Av. Price	-1.116***	-2.343***	-4.079***	-20.19***
	(0.1101)	(0.1557)	(0.2290)	(0.7160)
Time	-0.0033***	0.0115***	0.0091***	-0.0042
	(0.0004)	(0.0006)	(0.0008)	(0.0026)
Cat. Entropy	-0.0453	0.6336***	0.2329***	0.6125***
	(0.0560)	(0.0823)	(0.0372)	(0.0766)
Num. Comp. Stores	-0.0138**	-0.0055	0.1177***	0.3899***
	(0.0054)	(0.0034)	(0.0098)	(0.0270)
Num. Chain Own Stores	0.0826***	0.4104***		
	(0.0193)	(0.0251)		
SD Sh. Prod.	0.0524***	-0.0190***	0.0046	-0.0358***
	(0.0039)	(0.0028)	(0.0031)	(0.0049)
Log Pop.	-0.0133**	-0.1083***	-0.0068	-0.1045*
	(0.0056)	(0.0420)	(0.0081)	(0.0566)
Unemp. Rate	0.1633	0.8016***	4.948***	0.3920
	(0.2614)	(0.2755)	(0.3677)	(0.4979)
Log Income	0.6534***	0.9222***	0.1649	-0.9734***
	(0.0678)	(0.1014)	(0.1118)	(0.2726)
SD Income	$-2.07 \times 10^{-6***}$	$-1.17 \times 10^{-5***}$	$4.34 \times 10^{-6***}$	$-1.89 \times 10^{-5***}$
	(5.32×10^{-7})	(9.89×10^{-7})	(1.44×10^{-6})	(3.47×10^{-6})
Fixed-effects				
Product	Yes	Yes	Yes	Yes
Market-chain	Yes	Yes		
Month	Yes	Yes	Yes	Yes
Market			Yes	Yes
Fit statistics				
Observations	370,525	284,191	478,470	310,556
R^2	0.20964	0.18047	0.21770	0.30601
Within R^2	0.00438	0.01724	0.01193	0.08085

Clustered (Product-Time) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

B Product Characteristics

Product / Market	Brand	Specification*	% Share in CPI	Owner (/merger)	Sample Start (merge)
Beer	Patricia	0.96 L	0.38	FNC	2007/04
Beer	Pilsen	0.96 L	0.38	FNC	2007/04
Beer	Zillertal	1 L	0.38	FNC	2010/11
Wine	Faisán	1 L	0.80	Grupo Traversa	2007/04
Wine	Santa Teresa Clasico	1 L	0.80	Santa Teresa SA	2007/04
Wine	Tango	1 L	0.80	Almena	2007/04
Carbonated Soft Drink	Coca Cola	1.5 L	1.12	Coca Cola	2007/04
Carbonated Soft Drink	Nix	1.5 L	1.12	Milotur (CCU)	2007/04
Carbonated Soft Drink	Pepsi	1.5 L	1.12	Pepsi	2010/11
Still water	Matutina	2 L	0.81	Salus	2007/04
Still water	Nativa	2 L	0.81	Milotur (CCU)	2007/04
Still water	Salus	2.25 L	0.81	Salus	2007/04
Bread Loaf	Los Sorchantes	0.33 Kg	0.06	Bimbo / Los Sorchantes	2010/11 (2011/04
Bread Loaf	Bimbo	0.33 Kg	0.06	Bimbo	2010/11
Bread Loaf	Pan Catalán	0.33 Kg	0.06	Bimbo	2010/11
Brown eggs	Super Huevo	1/2 dozen	0.46	Super Huevo	2010/11
Brown eggs	El Jefe	1/2 dozen	0.46	El Jefe	2010/12
Brown eggs	Prodhin	1/2 dozen	0.46	Prodhin	2007/07
Butter	Calcar	0.2 Kg	0.23	Calcar	2007/04
Butter	Conaprole sin sal	0.2 Kg	0.23	Conaprole	2007/04
Butter	Kasdorf	0.2 Kg	0.23	Conaprole	2010/11

* Kg = kilograms; L = liters; M = meters. n/i - No information.

Product / Market	**Brand**	**Specification***	**% Share in CPI**	**Owner (/merger)**	**Sample Start (merge)**
Cacao	Copacabana	0.5 Kg	0.08	Nestlé	2007/04
Cacao	Vascolet	0.5 Kg	0.08	Nestlé	2007/06
Coffee	Aguila	0.25 Kg	0.14	Nestlé	2007/04
Coffee	Chana	0.25 Kg	0.14	Nestlé	2007/04
Coffee	Saint	0.25 Kg	0.14	Saint Hnos	2010/11
Corn Oil	Delicia	1 L	n/i	Cousa	2010/11
Corn Oil	Río de la Plata	1 L	n/i	Soldo	2010/11
Corn Oil	Salad	1 L	n/i	Nidera	2010/11
Dulce de leche	Conaprole	1 Kg	0.14	Conaprole	2007/04
Dulce de leche	Los Nietitos	1 Kg	0.14	Los Nietitos	2007/04
Dulce de leche	Manjar	1 Kg	0.14	Manjar	2007/04
Flour (corn)	Gourmet	0.4 Kg	n/i	Deambrosi	2010/11
Flour (corn)	Presto Pronta Arcor	0.5 Kg	n/i	Arcor	2010/11
Flour (corn)	Puritas	0.45 Kg	n/i	Molino Puritas	2010/11
Flour 000 (wheat)	Cañuelas	1 Kg	0.21	Molino Cañuelas	2010/11
Flour 000 (wheat)	Cololó	1 Kg	0.21	Distribuidora San José	2010/11
Flour 0000 (wheat)	Cañuelas	1 Kg	0.21	Molino Cañuelas	2007/04
Flour 0000 (wheat)	Cololó	1 Kg	0.21	Distribuidora San José	2007/04
Flour 0000 (wheat)	Primor	1 Kg	0.21	Molino San José	2010/11
Grated cheese	Conaprole	0.08 Kg	0.16	Conaprole	2007/04
Grated cheese	Artesano	0.08 Kg	0.16	Artesano	2010/11
Grated cheese	Milky	0.08 Kg	0.16	Milky	2007/04
Deodorant	Axe Musk	0.105 Kg	0.34	Unilever	2010/11
Deodorant	Dove Original	0.113 Kg	0.34	Unilever	2010/11
Deodorant	Rexona Active Emotion	0.100 Kg	0.34	Unilever	2010/11

* Kg = kilograms; L = liters; M = meters. n/i - No information.

Product / Market	Brand	Specification*	% Share in CPI	Owner (/merger)	Sample Start (merge)
Hamburger	Burgy	0.2 Kg	n/i	Schneck	2010/11
Hamburger	Paty	0.2 Kg	n/i	Sadia Uruguay	2010/11
Hamburger	Schneck	0.2 Kg	n/i	Schneck	2010/11
Ice Cream	Conaprole	1 Kg	0.22	Conaprole	2010/11
Ice Cream	Crufi	1 Kg	0.22	Crufi	2010/11
Ice Cream	Gebetto	1 Kg	0.22	Conaprole	2010/11
Margarine	Flor	0.2 Kg	n/i	Cousa	2010/11
Margarine	Doriana nueva	0.25 Kg	n/i	Unilever	2007/04
Margarine	Primor	0.25 Kg	n/i	Cousa	2007/04
Mayonnaise	Fanacoa	0.5 Kg	0.21	Unilever	2007/04
Mayonnaise	Hellmans	0.5 Kg	0.21	Unilever	2007/04
Mayonnaise	Uruguay	0.5 Kg	0.21	Unilever	2007/04
Noodles	Cololo	0.5 Kg	0.43	Distribuidora San José	2007/07
Noodles	Adria	0.5 Kg	0.43	La Nueva Cerro	2007/07
Noodles	Las Acacias	0.5 Kg	0.43	Alimentos Las Acacias	2007/07
Peach jam	Dulciora	0.5 Kg	n/i	Arcor	2007/04
Peach jam	El Hogar	0.5 Kg	n/i	Lifibel SA	2010/11
Peach jam	Los Nietitos	0.5 Kg	n/i	Los Nietitos	2007/04
Peas	Campero	0.3 Kg	0.09	Regional Sur	2010/11
Peas	Cololó	0.3 Kg	0.09	Distribuidora San José	2010/11
Peas	Nidemar	0.3 Kg	0.09	Nidera	2010/11
Rice	Aruba tipo Patna	1 Kg	0.38	Saman	2007/04
Rice	Blue Patna	1 Kg	0.38	Coopar	2007/04
Rice	Green Chef	1 Kg	0.38	Coopar	2007/04
Rice	Pony	1 Kg	0.38	Saman	2010/11

* Kg = kilograms; L = liters; M = meters. n/i - No information.

Product / Market	Brand	Specification*	% Share in CPI	Owner (/merger)	Sample Start (merge)
Rice	Vidarroz	1 Kg	0.38	Coopar	2008/05
Rice	Saman Blanco	1 Kg	0.38	Saman	2010/11
Crackers	Famosa	0.14 Kg	0.28	Mondelez	2007/04
Crackers	Maestro Cubano	0.12 Kg	0.28	Bimbo	2007/04
Salt	Sek	0.5 Kg	0.09	Deambrosi	2007/04
Salt	Torrevieja	0.5 Kg	0.09	Torrevieja	2007/04
Salt	Urusal	0.5 Kg	0.09	UruSal	2007/04
Semolina pasta	Adria	0.5 Kg	0.43	La Nueva Cerro	2007/07
Semolina pasta	Las Acacias	0.5 Kg	0.43	Alimentos Las Acacias	2007/07
Semolina pasta	Puritas	0.5 Kg	0.43	Molino Puritas	2010/11
Soybean oil	Condesa	0.9 L	0.11	Cousa	2008/05
Soybean oil	Río de la Plata	0.9 L	0.11	Soldo	2010/11
Soybean oil	Salad	0.9 L	0.11	Nidera	2010/11
Sugar	Azucarlito	1 Kg	0.35	Azucarlito	2007/04
Sugar	Bella Union	1 Kg	0.35	Bella Unión	2007/04
Sunflower oil	Optimo	0.9 L	0.37	Cousa	2007/04
Sunflower oil	Uruguay	0.9 L	0.37	Cousa	2007/04
Sunflower oil	Río de la Plata	0.9 L	0.37	Soldo	2010/11
Tea	Hornimans	Box (10 units)	0.08	José Aldao	2007/04
Tea	La Virginia	Box (10 units)	0.08	La Virginia	2007/04
Tea	President	Box (10 units)	0.08	Carrau	2010/11
Tomato paste	Conaprole	1 L	0.16	Conaprole	2007/04
Tomato paste	De Ley	1 L	0.16	Deambrosi	2007/04
Tomato paste	Gourmet	1 L	0.16	Deambrosi	2010/11
Yerba	Canarias	1 Kg	0.64	Canarias	2007/04

* Kg = kilograms; L = liters; M = meters. n/i - No information.

Product / Market	Brand	Specification*	% Share in CPI	Owner (/merger)	Sample Start (merge)
Yerba	Del Cebador	1 Kg	0.64	Molino Puritas	2007/06
Yerba	Baldo	1 Kg	0.64	Canarias	2010/11
Yogurt	Conaprole	0.5 Kg	0.13	Conaprole	2010/11
Yogurt	Parmalat (Skim)	0.5 Kg	0.13	Parmalat	2010/11
Yogurt	Calcar (Skim)	0.5 Kg	0.13	Calcar	2010/11
Bleach	Agua Jane	1 L	0.16	Electroquímica	2007/04
Bleach	Sello Rojo	1 L	0.16	Electroquímica	2007/04
Bleach	Solucion Cristal	1 L	0.16	Vessena SA	2007/04
Dishwashing detergent	Deterjane	1.25 L	0.13	Clorox Company	2007/04
Dishwashing detergent	Hurra Nevex Limon	1.25 L	0.13	Unilever	2007/04
Dishwashing detergent	Protergente	1.25 L	0.13	Electroquímica	2010/11
Laundry soap	Drive	0.8 Kg	0.45	Unilever	2007/04
Laundry soap	Nevex	0.8 Kg	0.45	Unilever	2007/04
Laundry soap	Skip, Paquete azul	0.8 Kg	0.45	Unilever	2007/04
Laundry soap, in bar	Bull Dog	0.3 Kg (1 unit)	n/i	Unilever	2007/04
Laundry soap, in bar	Nevex	0.2 Kg (1 unit)	n/i	Unilever	2007/04
Laundry soap, in bar	Primor	0.2 Kg (1 unit)	n/i	Soldo	2010/11
Shampoo	Fructis	0.35 L	0.36	Garnier	2007/04
Shampoo	Sedal	0.35 L	0.36	Unilever	2007/04
Shampoo	Suave	0.93 L	0.36	Unilever	2007/04
Soap	Astral	0.125 Kg	0.16	Colgate	2010/11
Soap	Palmolive	0.125 Kg	0.16	Colgate	2007/04
Soap	Rexona	0.125 Kg	0.16	Unilever	2012/12
Toilet paper	Higienol Export	4 units (25 M each)	0.24	Ipusa	2007/04
Toilet paper	Elite	4 units (25 M each)	0.24	Ipusa	2010/11

* Kg = kilograms; L = liters; M = meters. n/i - No information.

Product / Market	Brand	Specification*	% Share in CPI	Owner (/merger)	Sample Start (merge)
Toilet paper	Sin Fin	4 units (25 M each)	0.24	Ipusa	2007/04
Toothpaste	Pico Jenner	0.09 Kg	0.19	Abarly / Colgate	2010/11 (2012/07
Toothpaste	Colgate Herbal	0.09 Kg	0.19	Colgate	2010/11
Toothpaste	Kolynos	0.09 Kg	0.19	Colgate	2010/11

* Kg = kilograms; L = liters; M = meters. n/i - No information.