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. Next, we analyze the effect of two sources of price dispersion: differences in the assortment of products in a category and differences in the competitive environment of stores. We found that assortment differences substantially and increasingly affect price dispersion over time. Store competition has a static effect on price dispersion but a limited effect in the long-run price dispersion. Chains' price dispersion due to the exposure to other stores of the same chain in a market is as strong as independent stores' reaction to competitors in the same market, pointing to evidence of price discrimination strategies by chains. Chains' price response to competition from other stores is minimal, either static or over time.

JEL CODES: D22, D4, F40, L1, L81.

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*This is a substantially revised version of the paper "Long Run Price or Variety Convergence?". Codes are available at https://github.com/LeandroZipitria/Convergence.

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1 Introduction

There is ample evidence of long-run price convergence in the literature. Within countries, it has been found by 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, among others. 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. 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 convergence is due mainly to the reduction in trade costs.[1] Sellers react to this reduction in trade cost by discriminating against consumers to partially offset price convergence between different markets, such as by offering various products (Dvir and Strasser, 2018).

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 do not analyze the evolution of price dispersion and how the different factors affect it in the long-run.

In this paper, we document an increase in price dispersion in retail markets in Uruguay over time. Using a detailed database for a limited number of products, we found prices to divert by 0.0134% standard deviation each month. The divergence is mainly due to the pricing decisions of stores in different chains. Next, we study the effect of two forces on prices' long-run dispersion. Previous work has shown that store category assortment differs (Hwang, Bronnenberg, and Thomadsen, 2010; DellaVigna and Gentzkow, 2019).

[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).

We define a simple entropy index to measure the extent of similarity of products offered by stores. This index is calculated at the category level—i.e., beer—as usually defined in the literature (Nakamura, 2008). This analysis emphasizes the role of competition between products rather than between stores (Kaplan, Menzio, Rudanko, and Trachter, 2019). The second force that may affect prices' long-run dispersion is store competition. We count the number of stores in a given time and geographical area to measure the long-run impact on prices.

Our results suggest that both variables add to price dispersion. Still, that assortment variation has a robusts long-run effect: one standard deviation increase in the category assortment index increases long-run price dispersion by half. We next turn to the analysis of long-run price dispersion by chains. We found an increase in long-run price dispersion in independent stores but none within chains. Chains increase price dispersion if more stores of the same chain are in the market but not if they are competitors —evidence of price discrimination in chains—while independent stores react strongly to competitors. Lastly, category assortment has a strong long-run positive impact on price dispersion for independent stores but not for chains.

The paper contributes to two different strands of the literature. First, we contribute to the international economic literature by showing evidence of increasing price dispersion in a small open economy. We introduce two sources of price dispersion, evaluate their long-run impact, and the differentiated effect on convergence of stores being 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 does not analyze changes over time in its components. We provide evidence of how these two sources—store competition and assortment dispersion—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 convergence to the law of one price (LOP). One studied the half-life of prices to convergence (e.g., Elberg, 2016), while 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. 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 and decomposes the price variance across markets, stores, and within stores (pp. 309).

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 over fourteen years, one of the most prolonged retail prices databases in the literature.[2] 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 evaluating price dispersion and the forces driving price dispersion. For a given price, we have information on the market—location—the product and category (i.e., Pilsen 1 liter beer), the store chain, and the exact time the price is available.

Fixing time, product, and markets implies that only two different sources of price changes could affect the prices between stores for a given product through time: chains and categories. First, according to DellaVigna and Gentzkow (2019), retailers set the same prices for the same product. Dispersion within chain stores should be lower than between stores in a different or no chain. Changes in dispersion could be due to differences in competition between stores—i.e., mergers and management changes, which will affect the dispersion of prices between chains or stores. Secondly, there could be changes in

[2] The database does not have information on groceries.

the competitive environment of products—such as the entry of new products to a specific store's market or technological changes—that will affect products within a given category.

The paper is structured as follows. Section 2 presents detailed information of the database. Section 3 presents the empirical analysis and the results of the estimations of the price dispersion and the forces behind it. Section 4 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.[3] Moreover, the DGC is responsible for enforcing the Consumer Protection Law. 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 value-added tax rates (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 and stores across the country. The DGC issued Resolution Number 061/006, which mandates that grocery stores and 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 posted in the stores. In this regard, 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.

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

The data includes daily prices from April 1st of, 2007, to December 31th of, 2021 for 154 products, most of them defined by UPC. This detailed information allows us to track the same good in stores nationwide, avoiding measurement problems resulting from different products being compared (see the discussion in Atkin and Donaldson, 2015). The markets included in the sample represent 15.6% of the 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.[4]

The three best-selling brands are reported for each market, disregarding the store's brands.[5] Products were selected after a survey of some of the largest store chains in the year 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 markets. The 154 products in the database represent more than 60 markets defined at the product category level (e.g., sunflower oil and corn oil and 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 A.

For each store we have detailed information about the exact location given by its Universal Transverse Mercator (UTM) as well as about whether it belongs to a chain and the number of cashiers. The database has information for up to 512 stores—i.e., a non-balanced panel—across all nineteen political states, comprising 54 cities. Montevideo, the

[4]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.

[5]Exceptions are sugar, crackers, and cocoa, which has only two brands, and rice, which has up to six brands.

capital city of Uruguay, is also the country's largest city, with nearly forty percent of the Uruguayan population and 54% of all stores in the sample.[6] In the analysis in Section 3 we define each city as a market, except for Montevideo where we define a neighborhood as a market.

We identify 125 products out of 154 that could be exactly matched. We delete products that are not sold packaged (e.g., ham, meat, and poultry). Our final database has 125 products corresponding to 42 categories. For the selected goods the database has nearly 142 million daily observations. We delete outliers defined as those prices greater than 3 times or less than one third the median monthly price for each product (less than 0.01%). We then calculate the mode monthly price (Eichenbaum, Jaimovich, and Rebelo, 2011) for each product. Our final database is composed by 4,556,002 observations. Table 1 below shows descriptive statistics of the database and of the variables to be used in the analysis.

Table 1: Summary Statistics.

	Mean	St. D
Adjusted Log Price	-1.337	0.544
St. D. (CPI Adjusted Log Price)	0.055	0.064
Category Entropy	0.259	0.333
Number of Competing Stores*	2.545	3.587
Sample Period	04/2007	12/2021
Number of Observations	4,556,002	
Number of Stores	512	
Number of Chains	22	
Number of Markets (location)	117	
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 2010.
*Is the numer of stores in the same market and time.

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

3 Empirical Strategy

We measure price dispersion with the standard deviation of log Consumer Price Index (CPI) adjusted prices (Dvir and Strasser, 2018).[7] The equation for estimating price dispersion across time is:[8]

$$SD_{it}^{m} = \alpha + \alpha_i + \alpha^m + \beta \tilde{p}_{it}^{m} + \gamma t + \epsilon_{it}^{m}, \tag{1}$$

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^m are market-dummies, and ϵ_{it}^{m} is an error term. Table 2 below shows the estimation of Equation 1, with standard errors clustered at the product-time level.

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, we add a time square to find that the dispersion is increasing in time. Nevertheless, we estimate equations only with a linear trend in the following analysis to make interpretation easier.

Which are the sources of the increase in price dispersion over time? We propose to analyze two different sources: store assortment differences in categories and differences in competition between stores. In Borraz and Zipitría (2022) we show that if two stores differ in their products, then the convergence of prices for the common product is unlikely. The diversity of categories between stores shows the diversity in the competition within a store for products in a given category. 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

[7] Monthly average inflation was 0.65%, and prices tripled.

[8] Dvir and Strasser (2018) also introduce a quadratic trend in their analysis. In Table 2 we present the results for the linear trend but also include a quadratic trend.

Table 2: Convergence Baseline Estimation.

Dependent Variable:	SD (in %)				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Constant	1.239***				
	(0.0719)				
Av. Price	-2.048***	-8.605***	-1.971***	-7.733***	-7.659***
	(0.0423)	(0.2031)	(0.0421)	(0.2005)	(0.1994)
Time	0.0161***	0.0129***	0.0165***	0.0134***	0.0055***
	(0.0005)	(0.0004)	(0.0005)	(0.0004)	(0.0014)
Time2					4.18×10^{-5}***
					(8.09×10^{-6})
Fixed-effects					
Product		Yes		Yes	Yes
Market			Yes	Yes	Yes
Fit statistics					
Observations	943,461	943,461	943,461	943,461	943,461
R^2	0.04637	0.14481	0.11979	0.21197	0.21216
Within R^2		0.04363	0.04779	0.04069	0.04092

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

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. The mean $E_{it}^{m,c}$ in the database is 0.2585 and the standard deviation is 0.333. For stores, 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 2.5 and the standard deviation is 3.6. Next, we add our two variables to Equation 1 in Equation 2 and their interaction with the trend in Equation 3:

$$SD_{it}^m = \alpha + \alpha_i + \alpha^m + \beta \tilde{p}_{it}^m + \eta E_t^{m,c} + \theta N_t^m + \gamma t + \epsilon_{it}^m, \tag{2}$$

$$SD_{it}^m = \alpha + \alpha_i + \alpha^m + \beta \tilde{p}_{it}^m + \eta_1 E_t^{m,c} + \eta_2 t E_t^{m,c} + \theta_1 N_t^m + \theta_2 t N_t^m + \gamma t + \epsilon_{it}^m. \tag{3}$$

The Table 3 below shows the estimations of Equations 2 and 3, with standard errors clustered at the product-time level.

Columns (1) and (2) show that diverse category assortments or more stores in the market increase structural price dispersion. In standard deviation terms, Column (1) shows that an increase in one standard deviation in the category entropy (0.333) translates into an increase in dispersion of about 0.281 (0.333×0.8448) at the product level, more than four times the standard deviation of overall adjusted log prices (0.064). Or in time dispersion, one standard deviation of the category entropy equals the passage of 21 month (0.281/0.0131). The effect of store competition is four times larger: one standard deviation in the number of stores (3.587) increases price dispersion by 0,789 (3.587×0.2201), twelve times the standard deviation of overall adjusted log prices. In time terms, one standard deviation of the number of stores increases the price dispersion the same as 64 months (0.789/0.0123). Column (3) shows a slight decrease in both category dispersion and competition when both are in the estimation, which shows some degree of influence in the decisions of store assortment due to the competitive environment.

The trend coefficient does not change when controlling for the dispersion of products within categories—Column (1)—and decreases slightly with store competition—Column (2). Columns (4) to (6) of Table 3 add interaction terms of the entropy and competition measures with the time trend. Results show that competition and entropy have very different *temporal* effects. Competition effects are very temporal limited and two orders of magnitude lower than the time trend (0.0004 vs 0.0108 in Column (5) and 0.0002 vs 0.0078 in Column (6)). On the contrary, the effect of category dispersion is nearly one and a half higher on price dispersion than the effect of the time trend (0.0123 vs 0.009 in

Table 3: Source of Relative Convergence.

Dependent Variable:	SD (in %)					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Av. Price	-7.787***	-7.793***	-7.833***	-7.666***	-7.779***	-7.715***
	(0.2007)	(0.2011)	(0.2012)	(0.2002)	(0.2011)	(0.2008)
Time	0.0131***	0.0123***	0.0122***	0.0090***	0.0108***	0.0078***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Cat. Entropy	0.8448***		0.7497***	-0.3341***		-0.3280***
	(0.0348)		(0.0348)	(0.0674)		(0.0707)
Number Comp. Stores		0.2201***	0.1930***		0.1599***	0.1625***
		(0.0078)	(0.0077)		(0.0086)	(0.0089)
Time x Cat. Entropy				0.0123***		0.0113***
				(0.0007)		(0.0008)
Time x Number Comp. Stores					0.0004***	0.0002***
					(3.08×10^{-5})	(3.33×10^{-5})
Fixed-effects						
Product	Yes	Yes	Yes	Yes	Yes	Yes
Market	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	943,461	943,461	943,461	943,461	943,461	943,461
R^2	0.21343	0.21332	0.21446	0.21432	0.21345	0.21530
Within R^2	0.04247	0.04234	0.04372	0.04355	0.04249	0.04474

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

Column (4) and 0.0113 vs 0.0078 in Column (6)).

Table 3 shows that, in the data analyzed, competition between stores has a large one-time impact on price dispersion. Assortment differences between stores increase price dispersion throughout time: Column (6) show that a one standard deviation change in category assortment increase the trend of price dispersion by one half on the lung run.[9]

3.1 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 to consider five components, as store-specific product dispersion cannot be studied. Previously we analyzed four of the sources of price dispersion. Nevertheless, 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 convergence analysis. Our database has two store types: independent stores and chain stores. We now replicate the previous analysis by splitting the sample by chains, SD_{it}^{m} is now $SD_{it}^{m,s}$.

The previous analysis has two limitations. First, the standard deviation for each market will not capture the whole chain pricing decision, as only stores belonging to the same market will be captured. We will control for chain fixed effects to capture this effect partially. Second, we need to gain information on between stores dispersion, which is partially hidden in the aggregate information presented before. The analysis allows for capturing dispersion within chains and between independent stores but not between chains and independent stores, as prices for the same chain will be added. We partially overcome this result by selecting markets with only one store for the same chain. Finally, we split our variable of competing number of stores in two: $NComp_t^m = \sum_{j \in J_t^m, j \notin S} \mathbf{1} - 1$,

[9] The standard deviation of the entropy index is 0.333. The effect over time on the trend is 0.0038 (0.333×0.0113). The trend is now 0.0116 ($0.0038 + 0.0078$), 1.49 times the trend.

which measures the number of stores for each time-market that does not belong to the same chain, 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. Table 4 below shows the estimation results, weighted by the total number of stores in each triple time-product-chain and standard errors clustered at the chain-time level.

Table 4: Convergence Estimation by Chains.

Dependent Variable:	SD (in %)					
Stores	Full sample	Chains	Indep.	Full sample	Chains	Indep.
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Av. Price	-0.6574***	-0.2822***	-1.874***	-2.718***	-1.376***	-7.569***
	(0.0329)	(0.0205)	(0.0825)	(0.1647)	(0.1146)	(0.4109)
Time	0.0027***	-0.0002	0.0126***	0.0020***	-0.0005	0.0102***
	(0.0004)	(0.0004)	(0.0008)	(0.0004)	(0.0004)	(0.0007)
Fixed-effects						
Chain	Yes	Yes	Yes	Yes	Yes	Yes
Product				Yes	Yes	Yes
Market				Yes	Yes	Yes
Fit statistics						
Observations	912,836	655,818	257,018	912,836	655,818	257,018
R^2	0.24293	0.07529	0.03643	0.29403	0.11729	0.19220
Within R^2	0.01017	0.00336	0.03643	0.01038	0.00500	0.03157

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

Results show a very different picture for chains and independent stores. In line with DellaVigna and Gentzkow (2019), results for dispersion within chains shows stability, as neither time coefficient is significant—Columns (2) and (5). Divergence for independent stores, a proxy of between stores' relative price convergence, shows a coefficient slightly lower than the one in Column (4) of Table 2. Finally, the main result is in Columns (1) and (4) which show a divergence estimation nearly six times lower than the estimation in Column (4) of Table 2. Much of the difference between the time coefficient in both tables could be attributed to price dispersion between chains.

We now turn to the estimation of Equation 2 for chains with product-dummies and market-dummies, and adding interactions between $E_t^{m,c}$, N_t^m, and $N_t^{m,s}$ with the linear trend t. Table 5 below shows the estimations, weighted by the total number of stores in each triple time-product-chain and standard errors clustered at the chain-time level, with no interactions with the trend, while Table 6 shows the interaction with the trend.

The Table 5 shows that the times coefficient remains mostly unchanged after controlling for assortment variation and competition in comparison to Columns (4) to (6) of Table 4. Controls for competing stores show for Chains the emergence of a trend towards convergence (Columns (5) and (8)). For independent stores, the time coefficient remains mainly unchanged in magnitude, although it slightly increases when controlling for the number of competing stores in relation to category dispersion. The difference in the estimated time coefficient for the full sample in Column (7)—0.0023—and the time coefficient in Column (3) of Table 3—0.0122—points again to the role of competition between chains on price dispersion. This is also confirmed in Table 5 for independent stores, where the trend coefficient in line with the the time coefficient in Column (3) of Table 3.

The estimated coefficients for category dispersion are in line with those estimated in Table 3 above, but the variable has a stronger effect in independent stores than within chains (Columns (2) and (3)). The role of other competing stores shows how chains react to—loosely defined—competition. Column (5) and (8) show that chains respond much strongly to stores of the same chain in the market than to competitors. The coefficient of own stores is seven times higher than the number of competitors' stores. This results point to a strategy of price discrimination by stores by varying the prices of similar products to consumers in the same geographical market. On the contrary, independent stores react more strongly to competing stores than chains.

Next, in Table 6 below, we explore the interaction of the independent variables with the time trend.

Columns (1) to (3) show the role of assortment dispersion between stores on price volatility across time. Interestingly, the coefficient for independent stores is 1.3 times

Table 5: Source of Relative Convergence in Chains (Linear Trend).

Dependent Variable:					SD (in %)				
Stores	Full sample	Chains	Indep.	Full sample	Chains	Indep.	Full sample	Chains	Indep.
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables									
Av. Price	-2.751***	-1.398***	-7.590***	-2.736***	-1.397***	-7.651***	-2.765***	-1.414***	-7.658***
	(0.1628)	(0.1140)	(0.4082)	(0.1651)	(0.1159)	(0.4111)	(0.1633)	(0.1155)	(0.4089)
Time	0.0023***	-0.0003	0.0107***	0.0017***	-0.0009**	0.0089***	0.0021***	-0.0008*	0.0095***
	(0.0004)	(0.0004)	(0.0007)	(0.0004)	(0.0004)	(0.0007)	(0.0004)	(0.0004)	(0.0007)
Cat. Entropy	0.9784***	0.6322***	0.7570***				0.9315***	0.5402***	0.6585***
	(0.0494)	(0.0644)	(0.0757)				(0.0503)	(0.0652)	(0.0649)
Number Comp. Stores				0.0180***	0.0237***	0.2065***	0.0150***	0.0228***	0.1800***
				(0.0047)	(0.0045)	(0.0377)	(0.0046)	(0.0044)	(0.0359)
Same Chain Stores				0.1461***	0.1765***		0.1205***	0.1642***	
				(0.0107)	(0.0096)		(0.0109)	(0.0099)	
Fixed-effects									
Product	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chain	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics									
Observations	912,836	655,818	257,018	912,836	655,818	257,018	912,836	655,818	257,018
R^2	0.29612	0.11866	0.19337	0.29469	0.12008	0.19338	0.29657	0.12106	0.19424
Within R^2	0.01332	0.00654	0.03297	0.01131	0.00815	0.03298	0.01394	0.00925	0.03402

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

Table 6: Source of Relative Convergence in Chains (Interaction Trend).

Dependent Variable:					SD (in %)				
Stores	Full sample	Chains	Indep.	Full sample	Chains	Indep.	Full sample	Chains	Indep.
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables									
Av. Price	-2.703***	-1.391***	-7.553***	-2.731***	-1.388***	-7.642***	-2.717***	-1.405***	-7.603***
	(0.1603)	(0.1129)	(0.4076)	(0.1638)	(0.1167)	(0.4112)	(0.1601)	(0.1149)	(0.4081)
Time	0.0012***	-0.0005	0.0095***	0.0069***	-0.0048***	0.0201***	0.0054***	-0.0047***	0.0185***
	(0.0004)	(0.0004)	(0.0007)	(0.0007)	(0.0007)	(0.0012)	(0.0007)	(0.0007)	(0.0015)
Cat. Entropy	-0.1529	0.3080*	0.3479**				-0.1250	0.5038***	0.0370
	(0.1092)	(0.1578)	(0.1674)				(0.1121)	(0.1610)	(0.1649)
Time x Cat. Entropy	0.0129***	0.0036**	0.0047**				0.0119***	0.0011	0.0061***
	(0.0014)	(0.0016)	(0.0022)				(0.0014)	(0.0017)	(0.0022)
Number Comp. Stores				0.0854***	0.0263***	0.3711***	0.0807***	0.0292***	0.3433***
				(0.0101)	(0.0085)	(0.0444)	(0.0099)	(0.0084)	(0.0436)
Same Chain Stores				0.2787***	0.0527***		0.2285***	0.0350*	
				(0.0198)	(0.0178)		(0.0190)	(0.0182)	
Time x Number Comp. Stores				-0.0003***	-3.08×10^{-5}	-0.0013***	-0.0003***	-5.21×10^{-5}	-0.0012***
				(5.15×10^{-5})	(4.07×10^{-5})	(0.0002)	(5.12×10^{-5})	(4.09×10^{-5})	(0.0002)
Time $\times$ Same Chain Stores				-0.0011***	0.0013***		-0.0008***	0.0013***	
				(0.0002)	(0.0002)		(0.0002)	(0.0002)	
Fixed-effects									
Product	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chain	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics									
Observations	912,836	655,818	257,018	912,836	655,818	257,018	912,836	655,818	257,018
R^2	0.29699	0.11875	0.19347	0.29553	0.12173	0.19511	0.29806	0.12293	0.19591
Within R^2	0.01453	0.00664	0.03309	0.01248	0.01000	0.03506	0.01604	0.01136	0.03601

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

larger than those of chains. This result could be because assortments within stores are more similar. The mean entropy index for chains is 0.026, and the standard deviation is 0.126, while for independent stores, the mean entropy index is 0.131, and the standard deviation is 0.265.

The role of competitors is again different in time between chains and independent stores. There is no temporal effect of local competitors on chains (Columns (5) and (8)), evidence that the pricing decision should be central planned at the chain rather than market-specific (DellaVigna and Gentzkow, 2019). Chains are much more aware of other stores of the same chain in the area for setting prices, pointing again to a price discrimination strategy. Independent stores react to competitors by mimicking them, as the negative—but low—coefficient of the interaction between competing stores and time shows in Columns (6) and (9).

Lastly, Column (7) shows that the time coefficient decreases by a one third compared to Column (6) of Table 3. The role of dispersion between stores is much more limited when other factors are taken into account.

4 Conclusion

We analyze price dispersion in retail markets using a single, detailed, large-period database for a small open economy. Contrary to previous papers, we found retail prices to diverge in the long-run. We add two sources for price dispersion: store competition and variation in assortment in a category. Our results suggest that both variables increase price dispersion but that assortment variation has a strong long-run effect: one standard deviation increase in the category assortment index increases long-run price dispersion by half.

We next turn to the analysis of long-run price dispersion by chains. We found an increase in long-run price dispersion in independent stores but none within chains. Chains increase price dispersion if more stores of the same chain are in the market but not if they are competitors, while independent stores react strongly to competitors. Lastly, category assortment has a strong long-run positive impact on price dispersion for independent stores but not for chains.

Our results highlight how a store's pricing and assortment strategies impact long-run prices. While chains have relatively similar assortments, they use them to price-discriminate consumers in markets with more stores. Also, the analysis highlights how price dispersion sources change over time, showing that static analysis may miss vital information for understanding price evolution.

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A 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
Cacao	Copacabana	0.5 Kg	0.08	Nestlé	2007/04

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

Product / Market	Brand	Specification*	% Share in CPI	Owner (/merger)	Sample Start (merge)
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
Hamburger	Burgy	0.2 Kg	n/i	Schneck	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	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
Rice	Vidarroz	1 Kg	0.38	Coopar	2008/05

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

Product / Market	**Brand**	**Specification***	**% Share in CPI**	**Owner (/merger)**	**Sample Start (merge)**
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
Yerba	Del Cebador	1 Kg	0.64	Molino Puritas	2007/06

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

Product / Market	Brand	Specification*	% Share in CPI	Owner (/merger)	Sample Start (merge)
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
Toilet paper	Sin Fin	4 units (25 M each)	0.24	Ipusa	2007/04

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

Product / Market	**Brand**	**Specification***	**% Share in CPI**	**Owner (/merger)**	**Sample Start (merge)**
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.