Chain Pricing and Long-Run Retail Price Divergence*

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Abstract

Using UPC-level supermarket prices from Montevideo, Uruguay, from 2007 to 2024, this paper documents persistent long-run divergence in retail price dispersion within a single city. Price dispersion increases by approximately 3.4–3.5 percentage points over the sample period, equivalent to about four-fifths of its initial level. This increase appears across all margins of comparison: across markets, within markets, and within product–market cells.

The divergence is mainly a between-chain phenomenon. Within-chain price dispersion remains low and shows no systematic upward trend, while dispersion across chains is larger and increases persistently over time. We then show that different microeconomic features matter for different parts of this pattern. In the cross-section, local store competition is the strongest correlate of aggregate and between-chain dispersion levels. In the dynamics, however, competition is not systematically associated with faster dispersion growth. Instead, assortment differentiation is the characteristic most closely associated with different speeds of price-dispersion growth, especially in the aggregate and between-chain specifications. These results show that long-run retail price divergence reflects widening differences across chains and the evolution of product differentiation across local retail markets, even in a setting without currency, border, or regulatory frictions.

JEL Codes: D40, L11, L81, E31.

Keywords: Price Dispersion, Market Structure, Chain Pricing, Product Differentiation.

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1 Introduction

Retail prices for identical goods differ substantially across stores, even within narrowly defined local markets. This fact is central to models of consumer search, retail pricing, and market segmentation (Reinganum, 1979; Varian, 1980; Burdett and Judd, 1983; Stahl, 1989), and has been extensively documented in scanner and posted-price data (Lach, 2002; Sorensen, 2000; Kaplan and Menzio, 2015; Hitsch, Hortaçsu, and Lin, 2021; Berardi, Sevestre, and Thébault, 2017; Aursland, von Brasch, Holden, Wulfsberg, and Aas, 2020). Yet most of this evidence is cross-sectional or focuses on relatively short horizons. Much less is known about how retail price dispersion evolves over long time horizons, and whether its dynamics are shaped by the same market features that explain dispersion at a point in time.

This paper studies the long-run evolution of retail price dispersion using nearly eighteen years of UPC-level supermarket price data from Montevideo, Uruguay. We focus on three features of local retail markets: product assortment differentiation, local store competition, and retail-chain organization. These features are particularly relevant in supermarket retail markets, where consumers compare baskets rather than isolated products, and where chains may set prices centrally across stores.

The results can be summarized in four steps. First, price dispersion increases persistently over time. We measure dispersion as the cross-store standard deviation of CPI-adjusted log prices within product–market–month cells, expressed in percentage points. Over the sample period, dispersion rises by approximately 3.5 percentage points, equivalent to about four-fifths of its initial level. This increase appears across all margins of comparison: when we compare markets for the same product, when we follow markets over time, and when we restrict attention to changes within the same product–market cells. The evidence therefore points to broad-based long-run divergence rather than to a pattern driven by a particular product, market, or comparison margin.

Second, the divergence is primarily a between-chain phenomenon. Between-chain dispersion increases substantially over the sample period, while within-chain dispersion remains low and displays no systematic upward trend. Average within-chain dispersion is about one-seventh of between-chain dispersion. This pattern is consistent with evidence that retail chains often use uniform or zone-pricing rules that limit price variation across stores within the same chain (DellaVigna and Gentzkow, 2019; Adams and Williams, 2019). Thus, the long-run increase in local price dispersion does not mainly reflect chains increasingly differentiating prices across their own stores. It reflects widening price differences across chains operating in the same local markets.

Third, cross-sectional differences in dispersion are most strongly associated with local store competition. Markets with more competing seller units display higher aggregate and between-chain dispersion, especially when comparisons are made within markets or within product–market cells. Greater local competition, therefore, does not mechanically compress price differences across sellers. Instead, it is associated with greater relative price dispersion across chains, consistent with search-based models and evidence that a larger set of sellers may sustain, rather than eliminate, price dispersion (Varian, 1980; Lach, 2002; Kaplan, Menzio, Rudanko, and Trachter, 2019).

Fourth, the dynamics point to a different margin. Local store competition is associated with higher dispersion levels but not with faster growth in dispersion. The characteristic most closely related to differences in the speed of price-dispersion growth is within-category assortment differentiation. Markets with greater assortment differentiation experience faster growth in aggregate and between-chain dispersion over time. This is consistent with evidence that product variety and assortment choices affect price comparisons across sellers and that deviations from price convergence are measured (Borraz and Zipitría, 2022; Cavallo, Feenstra, and Inklaar, 2023). In this sense, long-run divergence is strongest where chains become more differentiated in the products they offer around common goods.

Setting. Montevideo provides a useful environment for studying these dynamics. It is a compact urban market within a single country, with a common currency and common national regulation. At the same time, supermarket retailing in Montevideo includes both independent stores and major chains, allowing price dispersion across all stores to be separated into within-chain and between-chain components. Our data, collected by the General Directorate of Commerce, covers 125 products across 42 product categories and identifies products, stores, neighborhoods, and chain affiliation.

Related literature. This paper contributes to four strands of research. The first strand studies the sources and persistence of price dispersion in retail markets. Classic search models show that price dispersion can arise in equilibrium even for homogeneous goods when consumers face search frictions or differ in their information and shopping behavior (Reinganum, 1979; Varian, 1980; Burdett and Judd, 1983). Empirically, price dispersion is large and persistent in retail markets, and is shaped by consumer search, store heterogeneity, product differentiation, and local market structure (Lach, 2002; Sorensen, 2000; Kaplan and Menzio, 2015; Hitsch, Hortaçsu, and Lin, 2021; Berardi, Sevestre, and Thébault, 2017; Sheremirov, 2020). Our contribution to this literature is to add a long-run perspective: we show that dispersion does not simply persist around a stable level, but increases systematically over time.

The second strand studies product variety, assortment differentiation, and the interpretation of price comparisons across stores. When stores differ in the set of products they offer, price comparisons for common products may reflect broader differences in positioning, product mix, consumer segments, and multiproduct search incentives (Kaplan and Menzio, 2015; Richards, Hamilton, and Allender, 2016; Handbury, 2021). Recent work shows that product variety and assortment choices affect measured deviations from price convergence (Borraz and Zipitría, 2022; Cavallo, Feenstra, and Inklaar, 2023). We build on this literature by showing that assortment differentiation is associated not only with cross-sectional price dispersion but also with its long-run dynamics. In our setting, markets with greater within-category assortment differentiation experience faster growth in price dispersion over time.

The third strand studies retail pricing and chain organization. Retail chains often set prices centrally, either uniformly across stores or through zone-pricing rules, which limit within-chain price variation and shift much of cross-store dispersion to differences across chains (DellaVigna and Gentzkow, 2019; Adams and Williams, 2019). Other work shows that local demand, costs, income, and neighborhood characteristics affect retail prices and product availability (Handbury and Weinstein, 2014; Handbury, 2021; Butters, Sacks, and Seo, 2022; Eizenberg, Lach, and Oren-Yiftach, 2021; Stroebel and Vavra, 2019). We contribute by showing that the distinction between within-chain and between-chain dispersion is not only relevant for explaining cross-sectional variation. It is central for understanding long-run divergence: between-chain dispersion is the component that increases persistently over time, while within-chain dispersion remains low and displays no comparable trend.

The fourth strand studies price convergence and deviations from the Law of One Price across locations. Existing work documents substantial but incomplete price convergence within countries and across countries, and emphasizes the role of trade costs, borders, distance, currency unions, and market integration (Parsley and Wei, 1996; O'Connell and Wei, 2002; Ceglowski, 2003; Fan and Wei, 2006; Parsley and Wei, 2001; Crucini and Shintani, 2008; Broda and Weinstein, 2008; Cavallo, Neiman, and Rigobon, 2014). Other papers document slow or incomplete convergence in specific markets, such as the automobile market (Gil-Pareja, 2003; Goldberg and Verboven, 2005; Dvir and Strasser, 2018). Our paper is related to this literature, but the mechanism is different. We study price divergence within a single urban retail market, where standard trade, currency, and regulatory frictions are largely absent. The evidence points not to international segmentation but to the organization of local retail markets.

Several studies analyze retail pricing in Uruguay using related data. Borraz and Zipitría (2012) document supermarket pricing behavior, while Klaczko (2025) studies retail price dispersion using a variance-decomposition approach. Borraz and Zipitría (2022) shows that product variety generates deviations from price convergence in Uruguay. We complement this work by focusing on the long-run evolution of dispersion and by separating the margins along which dispersion changes: across markets, within markets, within product–market cells, and across versus within retail chains.

Contributions. The paper makes three contributions to the literature. First, relative to studies that document price dispersion at a point in time or over short horizons, we study the long-run evolution of retail price dispersion and show that dispersion can increase persistently within a single urban market. Second, relative to work on uniform and zone pricing in retail chains, we show that chain organization matters not only for the level of dispersion but also for its trend: the long-run increase is concentrated between chains, while within-chain dispersion remains comparatively stable. Third, with respect to work on product variety and local market conditions, we show that assortment differentiation and local competition matter along different margins: competition is most closely associated with aggregate and between-chain dispersion levels, while assortment differentiation is more closely related to differences in the speed of dispersion growth.

Throughout the paper, we interpret the estimates as reduced-form associations rather than causal effects. Prices, product assortments, store entry, and chain pricing strategies are jointly determined in retail markets. The objective is therefore not to identify the structural effect of competition or assortment differentiation on price dispersion. Instead, we document how these endogenous features co-move with dispersion over time and across different margins of comparison: across markets, within markets, within product–market cells, and within versus between retail chains.

The remainder of the paper is organized as follows. Section 2 presents the data. Section 3 documents the long-run evolution of price dispersion. Section 4 studies the relationship between dispersion and cross-sectional market characteristics. Section 5 analyzes dynamic associations. Section 6 concludes.

2 Data

We perform the analysis using a detailed product-level database of daily posted prices compiled by the General Directorate of Commerce (DGC, by its Spanish acronym), a branch of Uruguay's Ministry of Economy and Finance.[1] Retailers are required to report posted prices under a sworn statement, so the data closely reflect posted in-store prices.

Supermarket sales in Uruguay are heavily concentrated in food and household consumption goods. In 2017, between 80 and 85 percent of total supermarket sales were grocery products—including food, personal care, and cleaning items—while the remaining 15 to 20 percent were non-food products such as textiles, appliances, toys, and household goods. Supermarket chains account for approximately 70 percent of retail sales. This composition underscores that our data capture the core of household consumption and that chain-level pricing strategies are economically central in the Uruguayan retail sector (Uruguay XXI, 2018).

The database contains daily prices from April 1, 2007, to December 31, 2024, for 154 products, the vast majority of which are identified at the UPC level. This level of detail allows us to track identical goods across stores and locations over time, avoiding measurement issues arising from product heterogeneity (Atkin and Donaldson, 2015). The products included represent 15.6% of the Uruguayan Consumer Price Index (CPI) basket. Products are defined so as to ensure comparability across stores, and each store must report the same specific variety throughout the sample period. For instance, all stores report Coca-Cola carbonated soft drinks in the 1.5-liter presentation. Prices are not reported when this particular variety is unavailable at the store.

Products were selected based on a 2006 survey of the largest store chains, with the three best-selling brands reported for each product category, excluding store brands. Some categories deviate from this rule: sugar, crackers, and cocoa include only two brands, while rice includes up to six. In November 2010, the product list was updated to revise brand

[1]This database updates and extends those used in Borraz and Zipitría (2012), Borraz, Cavallo, Rigobon, and Zipitría (2016), and Borraz and Zipitría (2022).

coverage across several categories and incorporate new products. Price information for discarded goods was removed, resulting in data loss for some markets. Overall, the 154 products span more than 60 product categories (e.g., sunflower oil and corn oil, or wheat flour 000 and wheat flour 0000, which differ in their baking uses). These categories define the within-category product environment used to measure assortment differentiation. For a small number of categories, such as meat and baguette, products are not identified at the UPC or brand level, and those categories were discarded. The complete list of products is reported in Online Appendix C.

We retain 125 products that can be consistently matched over time and exclude unpackaged goods such as ham, meat, and poultry, as well as drugstore items for which product coverage is incomplete. The resulting dataset contains 125 products across 42 categories and nearly 60 million daily price observations. We remove extreme outliers, defined as prices more than three times or less than one-third of the median monthly price for each product (i.e., less than 0.01% of observations).

To focus on regular prices and minimize the role of temporary sales, we compute monthly mode prices for each product-store pair. This approach is motivated by evidence that sales account for a substantial share of observed price dispersion, while reference prices display greater inertia (Nakamura, Nakamura, and Nakamura, 2011; Eichenbaum, Jaimovich, and Rebelo, 2011). We work at a monthly frequency both to summarize a long daily panel in a tractable way and to focus on persistent rather than high-frequency price dispersion. This is also consistent with Sheremirov (2020), who shows that inflation co-moves with regular-price dispersion.

The dataset includes detailed information on store characteristics, such as exact geographic location (Universal Transverse Mercator coordinates), chain affiliation, and the number of cashiers. While the data cover stores throughout Uruguay, most cities have too few stores to support a meaningful analysis of local price dispersion. Restricting attention to the small number of larger cities with multiple stores would also result in an uneven and difficult-to-interpret set of local markets. For this reason, we focus on Montevideo, Uruguay's capital and largest city, which accounts for nearly one-third of the population and 54% of stores in the sample. Geographic markets, in turn, are defined at the neighborhood level within Montevideo. The resulting unbalanced panel covers up to 324 stores.

Our final dataset consists of 3.2 million monthly price observations. Table 1 reports descriptive statistics and summarizes the variables used in the empirical analysis.

Table 1: Summary Statistics.

	Observations	Mean	Std. Dev.	Median
Panel A. Monthly store–product price data				
CPI-adjusted log price	3,257,937	3.283	0.548	3.257
Panel B. Product–market–month cells				
Price dispersion (%)	771,006	5.553	6.697	3.787
Average CPI-adjusted log price	1,143,448	3.248	0.548	3.215
Stores per product–market–month cell	1,143,448	2.849	2.802	2.000
Panel C. Market–month characteristics				
Category entropy	12,073	0.243	0.201	0.267
Log store competition	12,073	0.931	0.736	0.693
SD share of products	12,073	0.051	0.054	0.035
Log population density	12,073	8.647	1.001	8.820
Unemployment rate	9,917	0.078	0.034	0.073
Log real income	9,917	9.459	0.394	9.466
Panel D. Sample coverage				
Sample period				04/2007–12/2024
Monthly price observations				3,257,937
Stores				324
Products				125
Markets				61
Categories				42
Chains				22

Notes: Panel A reports summary statistics for the store–product–month price data. Panel B reports variables measured at the product–market–month level, the unit of observation in the baseline dispersion regressions. Price dispersion is the standard deviation of log CPI-adjusted prices across stores within each product–market–month cell, multiplied by 100, and is observed only when at least two stores report prices in a given cell. Panel C reports local market characteristics at the market–month level. Category entropy is computed at the category–market–month level and then averaged across categories within each market–month.

Our main unit of analysis is the product–market–month cell. A nontrivial share of these cells contains only one store, in which case price dispersion is not observed, and many others contain only two stores. Online Appendix Section A reports additional evidence on store coverage across markets and product–market cells. Online Appendix Figure A.1 shows that most market–month observations contain a small number of active stores, although a few markets have substantially larger store coverage. Online Appendix Figure A.2 shows the analogous distribution at the product–market–month level, which is the relevant unit for computing price dispersion. This distinction matters because a market may contain several active stores overall, but fewer stores selling a given product in a given month.

3 Price Dispersion over Time

This section documents the long-run evolution of local price dispersion. We first show that dispersion increases over time when comparing products and markets, and then examine whether this increase occurs within retail chains or across chains. We measure price dispersion as the cross-store standard deviation of log CPI-adjusted prices, expressed in percentage points, following Dvir and Strasser (2018). For each product i, market m, and month t, we compute SD_{imt} as the standard deviation across stores of log CPI-adjusted prices, multiplied by 100. We also compute $\tilde{p}_{imt}$, the corresponding cross-store average log CPI-adjusted price. Thus, SD_{imt} measures price dispersion across sellers for the same product in the same local market and month.

To study how price dispersion evolves over time, we estimate variants of the following specification:

$$SD_{imt} = \alpha + \beta \tilde{p}_{imt} + \gamma t + \delta' FE_{imt} + \varepsilon_{imt}, \tag{1}$$

where t is a linear monthly time trend and FE_{imt} denotes alternative sets of fixed effects. The coefficient of interest is γ, which measures the average change in local price dispersion over time under different comparisons induced by the fixed effects.

We begin with a specification without fixed effects, where γ captures the unconditional time evolution of price dispersion, pooling all product–market–month observations.

Adding product fixed effects changes the margin of comparison: γ is then identified from the evolution of dispersion within products, while still allowing comparisons across markets because markets are not held fixed. Thus, this specification captures the average time trend in dispersion for the same product across the set of local markets in which it is observed.

We then add market fixed effects. In this specification, persistent differences across markets are removed, so γ measures the average evolution of dispersion within markets over time, after accounting for product-level differences. Adding calendar-month fixed effects further restricts the comparison to the same calendar month across years, so that the estimated trend is not driven by common seasonal patterns in price dispersion.

Finally, we estimate specifications with product-by-market fixed effects. This specification changes the margin of comparison again: γ is identified from changes in dispersion over time within the same product–market cell. A positive estimate in this case implies that price dispersion for the same product in the same local market increases over time, rather than reflecting only differences across products or markets.

All specifications are estimated by weighted least squares, using the number of stores in each product-market-month cell as weights. Standard errors are two-way clustered by product category and market.

Table 2 reports the baseline results. The estimated coefficient on the time trend is positive and statistically significant in all specifications, indicating that retail price dispersion increases over time rather than converging. In Column (2), which includes product fixed effects, the coefficient is 0.0164; this compares the evolution of dispersion across markets and over time for the same product. In Column (3), which includes market fixed effects, the coefficient is 0.0167, indicating that dispersion also increases when comparisons are made within markets over time. Adding calendar-month fixed effects in Column (4) leaves the estimate unchanged, indicating that the trend is not driven by common seasonal patterns. Finally, Columns (5) and (6) include product-by-market fixed effects, so the trend is identified from changes in dispersion within the same product-market cell over time. The coefficient remains very similar, at 0.0166. Thus, the increase in dispersion is not confined to differences across products or markets: it is also present within markets and within product-market cells.

Over the 213-month sample period, these estimates imply an increase in price dispersion of approximately 3.5 percentage points.[2] This increase is economically meaningful: relative to the average dispersion observed during the first year of the sample, the estimated rise amounts to roughly four-fifths of the initial level.

Table 2: Baseline Price-Dispersion Trend Estimates.

Dependent Variable:	SD (in %)					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Constant	11.05***					
	(1.667)					
Av. Price	-2.107***	-7.359***	-6.864***	-6.853***	-5.994***	-5.981***
	(0.4910)	(1.510)	(1.431)	(1.433)	(1.263)	(1.265)
Time	0.0162***	0.0164***	0.0167***	0.0167***	0.0166***	0.0166***
	(0.0021)	(0.0022)	(0.0021)	(0.0021)	(0.0020)	(0.0020)
Fixed-effects						
Product		Yes	Yes	Yes		
Market			Yes	Yes		
Month				Yes		Yes
Product × Market					Yes	Yes
Fit statistics						
Observations	771,006	771,006	771,006	771,006	770,942	770,942
R^2	0.05764	0.17624	0.26022	0.26049	0.37652	0.37679
Within R^2		0.04869	0.05031	0.05029	0.05029	0.05028

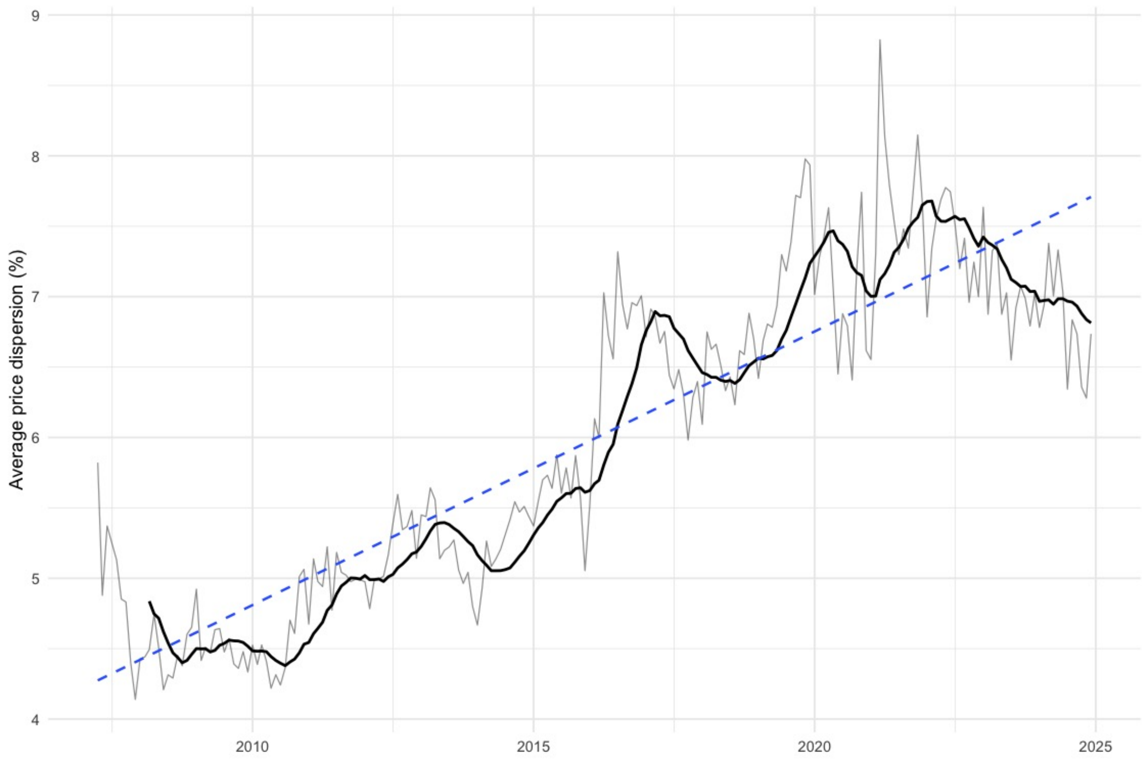
Clustered (category & Market) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The dependent variable is the cross-store standard deviation of log CPI-adjusted prices within each product-market-month cell, multiplied by 100. *Av. Price* is the corresponding cross-store average log price, and *Time* is a linear monthly trend. Product, market, month, and product-by-market fixed effects are included as indicated. Regressions are weighted by the number of stores in each cell. Standard errors are two-way clustered by product category and market.

[2] Since the sample contains 213 monthly periods, the change from the first to the last period corresponds to 212 monthly changes. Using the coefficient from Column (2), the implied increase is $0.0164 \times 212 = 3.48$ percentage points. Using the coefficient from Column (3), the implied increase is $0.0167 \times 212 = 3.54$ percentage points. The average level of price dispersion during the first 12 months of the sample is 4.34 percent, so these estimates correspond to approximately 80–82 percent of the initial dispersion.

Figure 1 provides a descriptive counterpart to the regression results. It plots the weighted monthly average of product-market price dispersion, together with a 12-month moving average and a fitted linear trend. The figure shows a clear upward movement in dispersion over the sample period. The increase is not perfectly monotonic: dispersion rises gradually during the first part of the sample, increases more sharply after the mid-2010s, reaches its highest levels around 2020–2022, and declines somewhat thereafter. Nevertheless, dispersion remains substantially above its initial level by the end of the sample period. This pattern is consistent with the positive and statistically significant time trends reported in Table 2.

Figure 1: Price Dispersion over Time.



Notes: The figure reports the weighted monthly average of product-market price dispersion. Price dispersion is measured as the standard deviation of log CPI-adjusted prices across stores within each product-market-month cell. The thin line reports the monthly series, the thick solid line reports a 12-month moving average, and the dashed line reports a fitted linear trend.

Online Appendix Table A.1 examines whether the increase in price dispersion is better described by a nonlinear time path. We re-estimate the baseline specifications, adding a quadratic time trend. The linear trend is kept in levels, as in the baseline specification, while the quadratic term is constructed as the squared deviation of the monthly time trend from its sample mean, divided by 10,000 for readability. Centering the quadratic term reduces the mechanical collinearity between the linear and squared components without changing the fitted time path. Across all margins of comparison, the coefficient on the centered quadratic term is small and statistically insignificant. At the same time, the linear trend remains positive, statistically significant, and very close to the baseline estimates, ranging from 0.0163 to 0.0166 in the fixed-effects specifications. Thus, the evidence does not support a meaningful quadratic pattern in the evolution of price dispersion.

We perform several robustness checks. First, although prices are CPI-deflated and the average price is included as a control in Equation 1, average prices may still display a time trend. To assess this possibility, Online Appendix Table A.2 re-estimates a version of Equation 1 using the average price as the dependent variable. Across all specifications, the estimated time coefficient is small and statistically insignificant, indicating no meaningful trend in average prices.

A second concern is that the baseline sample is not fixed, as new stores are added to the dataset over time. Online Appendix Figure A.3 describes the timing and spatial distribution of store entries across neighborhoods. Store entry is not uniform across local markets: two neighborhoods seem to have received more new stores than others, and entry is concentrated in specific periods. To assess whether this change in store composition drives the upward trend, Online Appendix Table A.3 restricts the sample to stores that were already present at the start of the sample period, in 2007. The coefficients remain statistically significant, with somewhat smaller magnitudes.

A third concern, related to store composition, is that the upward trend could be driven by a small set of markets with unusually high store entry. Online Appendix Figure A.4 shows that the distribution of stores per market-month shifted between the beginning and the end of the sample. Restricting the sample to stores observed at the beginning of the period addresses the possibility that newly observed stores follow different pricing policies, but it does not rule out the possibility that entry is spatially concentrated in particular markets. We therefore repeat the baseline estimates in Table 2 after excluding high-entry markets, defined as markets in the top decile of the distribution of store entry after the initial sample year. In our data, this corresponds to markets with six or more store entries. Online Appendix Table A.4 reports the results. The coefficients on the time trend remain statistically significant and of similar magnitude, indicating that the increase in price dispersion is not driven by markets with unusually high store entry rates.

A fourth concern is related to product composition. As noted in Section 2, the database underwent a major revision in November 2010, when nearly fifty products were added to the reporting system. The upward trend in dispersion could therefore partly reflect the entry of new products rather than changes in price dispersion after the product list stabilized. To address this concern, we repeat the baseline estimates, restricting the sample to 2011 onward, after the product-list revision, and excluding high-entry markets as defined above. Online Appendix Table A.5 reports the results. The coefficients on the time trend remain positive and statistically significant across all specifications and are, if anything, larger than in the baseline estimates. This suggests that the long-run increase in price dispersion is not driven by the inclusion of new products around the 2010 revision or by markets with unusually high store entry.

Having documented a persistent increase in local price dispersion, we now examine its heterogeneity. Since our data identify the chain affiliation of each store, we can decompose price dispersion into within- and between-chain components and assess whether the long-run increase reflects growing dispersion among stores belonging to the same chain or widening price differences across chains.

Retail chains play a central role in store-level price-setting behavior. A large body of evidence shows that stores within the same chain often follow uniform or zone-pricing policies and exhibit substantially less price dispersion than independent stores or stores belonging to different chains (Nakamura, Nakamura, and Nakamura, 2011; DellaVigna and Gentzkow, 2019). For this reason, distinguishing between-chain and within-chain dispersion is useful for interpreting the source of the divergence documented above. If the increase occurs mainly within chains, it would suggest that firms are increasingly allowing prices to vary across their own stores. If, instead, the increase occurs between chains, it would point to growing differences in pricing strategies across chains.

Our dataset contains both independent stores and stores belonging to retail chains. To distinguish price dispersion across chains from price dispersion across stores within the same chain, we construct two complementary databases.

First, we construct a within-chain database. We restrict the sample to stores belonging to retail chains, excluding independent stores. For each product i, market m, month t, and chain s, within-chain dispersion is defined as

$$SD^{\text{within}}_{imst} = 100 \times sd_{j \in J^s_{mst}} \left(p_{ijmt} \right),$$

where p_{ijmt} is the log CPI-adjusted price of product i in store j, market m, and month t, and J^s_{mst} is the set of stores belonging to chain s in market m and month t. The unit of observation in this database is therefore product–market–month–chain.

Second, we construct a between-chain database. For each product i, chain s, market m, and month t, we collapse stores belonging to the same chain into a single representative seller. We define

$$\tilde{p}_{ismt} = \text{median}_{j \in J^s_{mst}} \left(p_{ijmt} \right),$$

the median log CPI-adjusted price across stores belonging to chain s. Independent stores are kept as individual sellers, so for an independent store j, the representative price is simply its own price. Let G_{imt} denote the set of representative sellers for product i, market m, and month t, including one observation per chain and one observation for each independent store. Between-chain dispersion is then computed as

$$SD^{\text{between}}_{imt} = 100 \times sd_{g \in G_{imt}} \left(\tilde{p}_{igmt} \right).$$

This measure captures price differences across chains operating in the same product–

market–month cell, where each chain is represented once, and independent stores remain individual sellers.

Table 3: Price Dispersion Trends: Between- and Within-Chain Components.

Dependent Variable:	SD (in %)					
	Between chains			Within chains		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Av. Price	-9.451***	-9.107***	-7.792***	-2.219***	-1.634***	-1.542***
	(1.703)	(1.672)	(1.497)	(0.5806)	(0.4545)	(0.4480)
Time	0.0193***	0.0193***	0.0192***	-0.0002	0.0005	0.0006
	(0.0024)	(0.0023)	(0.0022)	(0.0014)	(0.0015)	(0.0015)
Fixed-effects						
Product	Yes	Yes		Yes	Yes	
Market		Yes			Yes	
Product × Market			Yes			Yes
Fit statistics						
Observations	648,399	648,399	648,318	513,346	513,346	513,319
R^2	0.21759	0.24032	0.36553	0.04086	0.13238	0.23111
Within R^2	0.06536	0.06319	0.06089	0.00996	0.00583	0.00533

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

Notes: The dependent variable is price dispersion, measured as the standard deviation of log CPI-adjusted prices, multiplied by 100. Columns (1)–(3) use the between-chain database: stores belonging to the same chain are collapsed into one representative seller at the product–chain–market–month level before computing dispersion at the product–market–month level. Columns (4)–(6) use the within-chain database: dispersion is computed across stores belonging to the same chain, so the unit of observation is product–market–month–chain. *Av. Price* is the corresponding average log CPI-adjusted price, and *Time* is a linear monthly trend. Product, market, and product-by-market fixed effects are included as indicated. Regressions are weighted by the number of seller units used to compute between-chain dispersion and by the number of stores used to compute within-chain dispersion. Standard errors are two-way clustered by product category and market.

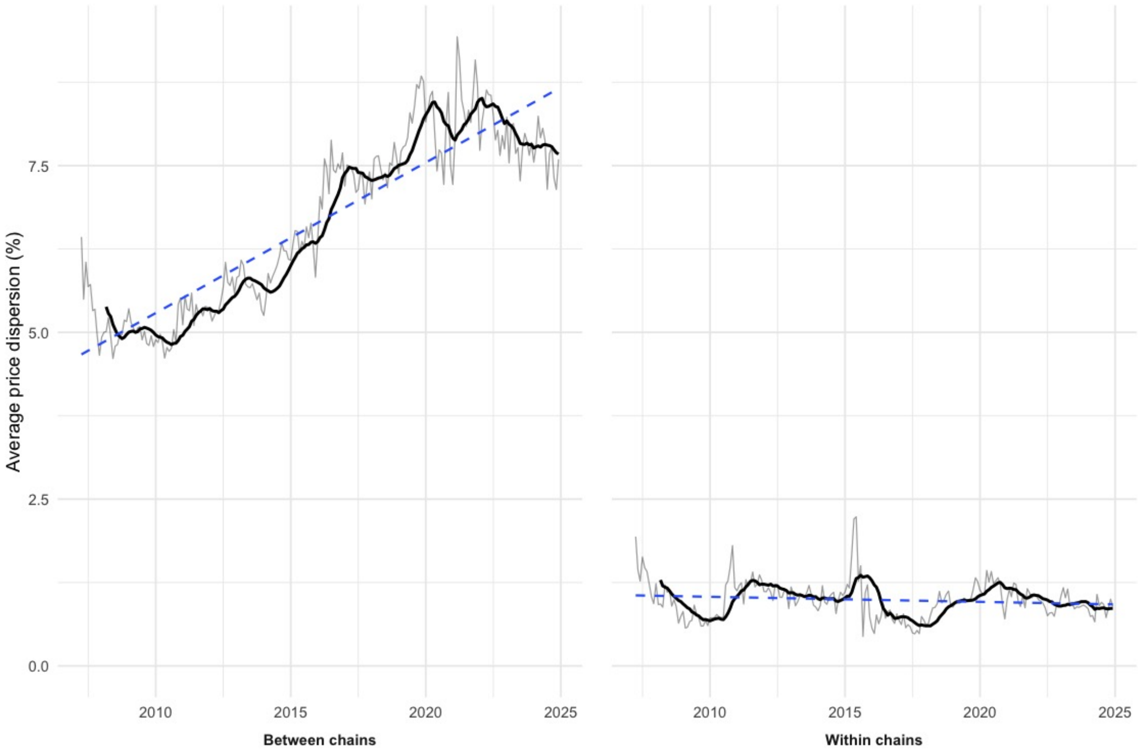
Table 3 compares the evolution of price dispersion across and within retail chains. Columns (1)–(3) are for the between-chain database, where dispersion is measured across representative chains within each product–market–month cell. The time trend is positive and statistically significant along all three margins of comparison. With product fixed effects, the coefficient is 0.0193, comparing the evolution of between-chain dispersion across markets and over time for the same product. Adding market fixed effects leaves the estimate unchanged, showing that between-chain dispersion also increases within markets over time. With product-by-market fixed effects, the coefficient is 0.0192, indicating that between-chain dispersion rises within the same product-market cells. These estimates are larger than the baseline trends in Table 2, which are around 0.0164–0.0167. Over the 213-month sample period, the between-chain estimates imply an increase in dispersion of about 4.1 percentage points, compared with roughly 3.5 percentage points in the baseline table.

Columns (4)–(6) are for the within-chain database, where the dependent variable is price dispersion across stores belonging to the same chain. In contrast to the between-chain results, the estimated time coefficients are close to zero and statistically insignificant. They range from -0.0002 to 0.0006, depending on the margin of comparison. Thus, there is no evidence that within-chain price dispersion increases over time. This conclusion holds when comparing within-chain dispersion across markets for the same product, within markets over time, and within product-market cells.

Taken together, the results indicate that the long-run increase in local price dispersion is driven by widening price differences among chains, rather than by chains increasingly differentiating prices across their own stores. The level of dispersion is also much larger across chains than within chains. Average within-chain dispersion is 0.96 percent, compared with 6.63 percent for between-chain dispersion. Thus, dispersion across chains is almost seven times as large as dispersion across stores belonging to the same chain. Treating chain-level differences only as nuisance variation would obscure the main margin along which price dispersion increases.

Figure 2 provides a graphical counterpart to these results. The figure plots the monthly evolution of between-chain and within-chain price dispersion, together with 12-month moving averages and fitted linear trends. The contrast between the two panels is clear. Between-chain dispersion increases substantially over the sample period, while within-chain dispersion remains low and displays no upward trend. This visual evidence reinforces the regression results: the long-run increase in local price dispersion is driven by widening price differences across chains, not by increasing dispersion among stores belonging to the same chain.

Figure 2: Price Dispersion over Time: Between and Within Chains.



Notes: The figure reports weighted monthly averages of between-chain and within-chain price dispersion. Price dispersion is measured as the standard deviation of log CPI-adjusted prices, multiplied by 100. The thin lines show the monthly series, the thick solid lines show 12-month moving averages, and the dashed lines show fitted linear trends.

The results in this section show that the increase in price dispersion is a broad and persistent feature of the data. It is not confined to comparisons across markets, nor does it disappear when we compare dispersion within markets or within product-market cells. The estimated time trend is remarkably stable across these alternative comparisons, indicating that price dispersion rises both across and within local retail markets.

The chain decomposition further shows that this divergence is primarily a between-chain phenomenon. Between-chain dispersion increases more rapidly than overall price dispersion. By contrast, within-chain dispersion remains low and shows no systematic upward trend. This suggests that retail chains tend to compress price differences across their own stores, while price differences across chains widen substantially over time. This pattern is related to evidence from Norwegian retail markets showing that store-level heterogeneity accounts for a substantial share of price variation (Aursland, von Brasch, Holden, Wulfsberg, and Aas, 2020). However, that analysis does not distinguish between within- and between-chain components, which is the margin emphasized here.

4 Price Dispersion and Market Structure

This section examines whether observable characteristics of local retail markets are associated with differences in price dispersion levels. The objective is descriptive: we examine whether markets with different retail structures display systematically higher or lower dispersion.

We extend Equation (1) to relate price dispersion to these observable market characteristics. The unit of observation remains a product–market–month cell. Let SD_{imt} denote price dispersion for product i in market m and month t, measured as the cross-store standard deviation of log CPI-adjusted prices, expressed in percentage points. Let Z_{imt} denote a set of microeconomic market characteristics relevant for local retail competition and product availability,[3] and let M_{mt} denote a vector of local socioeconomic controls measured at the market–month level, such as income and unemployment.

We estimate specifications of the form:

$$SD_{imt} = \alpha + \beta \tilde{p}_{imt} + \gamma t + \lambda' Z_{imt} + \theta' M_{mt} + \delta' FE_{imt} + \varepsilon_{imt}, \tag{2}$$

where $\tilde{p}_{imt}$ is the average log CPI-adjusted price in the product–market–month cell, t is a linear monthly time trend, and FE_{imt} denotes the same alternative sets of fixed effects used in Equation (1). The vector M_{mt} captures local socioeconomic conditions, while Z_{imt} captures microeconomic characteristics of the local retail environment. The coefficients λ measure how price dispersion varies with these microeconomic market char-

[3]Some microeconomic variables vary at the market–month–category level; in those cases, we assign the corresponding value to each product observation belonging to that category.

acteristics, conditional on average prices, the time trend, local socioeconomic controls, and the relevant fixed effects.

Based on the literature, we analyze three microeconomic market characteristics (Z_{imt}), which are typically endogenous to price dispersion. First, we measure differences in product assortments across stores within a product category. Borraz and Zipitría (2022) showed that when stores differ in the products offered within a category, convergence of prices for common products becomes less likely (see also Cavallo, Feenstra, and Inklaar, 2023). This mechanism emphasizes competition among products, consistent with defining markets at the product-category level (e.g., Nakamura, 2008; Kaplan and Menzio, 2015; Hitsch, Hortaçsu, and Lin, 2021) and with highlighting within-category differentiation (Kaplan and Menzio, 2015). Given limited products per category, we construct a category-level entropy index:

$$E_t^{m,c} = -\sum_{i \in c} \frac{N_i}{\sum_{i \in c} N_i} \ln \left(\frac{N_i}{\sum_{i \in c} N_i} \right),$$

where N_i is the number of stores offering product i in category c. Higher values indicate more diverse assortments across stores. Table 1 reports a mean category entropy of 0.243 and a standard deviation of 0.201 at the market–month level. We expect this association to be positive; i.e., larger differences in the products offered by stores in a given category imply greater price dispersion, due to differences in product competition intensity.

Second, we include variation in the total number of products offered by stores within a market. Borraz, Carozzi, González-Pampillón, and Zipitría (2024) showed that stores may strategically expand their assortments in response to neighborhood change. We measure within-market dispersion in store assortment size as the standard deviation of the share of products each store has over the number of products available each time:

$$SDP_t^m = sd_t^m \left(\frac{\#\text{products}_{jt}^m}{\#\text{products}_j} \right),$$

with mean 0.051 and standard deviation 0.054. We expect this coefficient to be positive;

i.e., larger differences in stores' total product counts—potentially reflecting differences in store size, or consumer sorting—imply greater price dispersion (Handbury, 2021).

Third, we measure differences in local store competition across markets. Following Berardi, Sevestre, and Thébault (2017), we define the number of competitors as

$$N_{mt} = \sum_{j \in J_{mt}} \mathbf{1} - 1,$$

where J_{mt} is the set of stores operating in market m at time t. In the regressions, we use $\log(1 + N_{mt})$ to reduce the influence of extreme values and to retain observations with no competitors. The mean value of log store competitors is 0.931, with a standard deviation of 0.736. More competition between stores has an ambiguous effect on price dispersion. On the one hand, greater competition may put pressure on prices to converge, as consumers can more easily compare prices across nearby stores. On the other hand, as the number of stores increases, consumers may face a larger set of price vectors and search costs may also increase (Varian, 1980; Lach, 2002). If the first effect dominates, the coefficient should be negative; if the second effect dominates, the coefficient should be positive.

We also consider three variables commonly used in the literature as controls, denoted by M_{mt}. We include the unemployment rate (UR^m_t, Daruich and Kozlowski 2023), log real income (Inc^m_t, Handbury 2021; Berardi, Sevestre, and Thébault 2017), and market size measured by population density (Pop^m_t, Handbury and Weinstein 2014; Berardi, Sevestre, and Thébault 2017; Daruich and Kozlowski 2023). The first two variables are computed over six-month windows at the neighborhood level. Population density is the monthly linear interpolation of the population for each market in the three Uruguayan censuses (2004, 2011, 2023) divided by the square kilometers of each market.

We cannot construct unemployment and income for all market–month cells because some neighborhoods have too few household survey observations. As a result, specifications with socioeconomic controls use a smaller sample. Importantly, this restriction selects a fixed set of neighborhoods: neighborhoods included in the controlled specifications are observed throughout the sample period, while excluded neighborhoods are omitted for the entire period.

Table 4: Price Dispersion and Local Market Characteristics.

Dependent Variable:	SD (in %)					
	Without Controls			With Controls		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Av. Price	-7.827***	-7.141***	-6.260***	-7.356***	-7.023***	-6.179***
	(1.518)	(1.422)	(1.251)	(1.464)	(1.419)	(1.258)
Time	0.0100***	0.0115***	0.0118***	0.0110***	0.0115***	0.0119***
	(0.0025)	(0.0023)	(0.0023)	(0.0026)	(0.0026)	(0.0025)
Cat. Entropy	1.655***	0.4924***	0.2630	1.417***	0.5203***	0.2828
	(0.3573)	(0.1823)	(0.1866)	(0.3471)	(0.1908)	(0.1973)
Log Store Competition	0.2420	1.742***	1.859***	0.8138***	1.730***	1.857***
	(0.2030)	(0.4010)	(0.3899)	(0.2559)	(0.3930)	(0.3772)
SD Sh. Prod.	14.96***	2.763	1.548	13.57***	2.846	1.495
	(3.797)	(2.364)	(2.198)	(3.386)	(2.463)	(2.285)
Log Pop. Density				-0.0553	1.858	1.413
				(0.2585)	(2.781)	(2.761)
Unemp. Rate				0.6542	2.971	2.746
				(2.556)	(1.887)	(1.793)
Log Real Income				-1.880***	-0.3484	-0.4392
				(0.6148)	(0.5738)	(0.5536)
Fixed-effects						
Product	Yes	Yes		Yes	Yes	
Market		Yes			Yes	
Product × Market			Yes			Yes
Fit statistics						
Observations	771,006	771,006	770,942	698,344	698,344	698,298
R^2	0.21016	0.26592	0.38132	0.22245	0.26390	0.37486
Within R^2	0.08785	0.05762	0.05759	0.09592	0.05832	0.05853

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

Notes: The dependent variable is the cross-store standard deviation of log CPI-adjusted prices within each product–market–month cell, multiplied by 100. *Av. Price* is the corresponding cross-store average log CPI-adjusted price, and *Time* is a linear monthly trend. The market characteristics are defined in the text. Columns (1)–(3) include only microeconomic market characteristics, while Columns (4)–(6) add unemployment, log real income, and log population density. Product, market, and product-by-market fixed effects are included as indicated. Regressions are weighted by the number of stores in each product–market–month cell. Standard errors are two-way clustered by product category and market.

Table 4 relates price dispersion levels to local market characteristics. The first three columns include only microeconomic market characteristics, while Columns (4)–(6) add local socioeconomic variables and population density. The clearest cross-sectional correlate is local store competition. A one-standard-deviation increase in log store competition, 0.736, is associated with about 0.60 percentage points higher dispersion across markets, 1.27 percentage points higher dispersion within markets, and 1.37 percentage points higher dispersion within product–market cells. Thus, markets with more competing stores display higher price dispersion, especially when comparisons are made within markets or within product–market cells. This pattern is consistent with search-based models in which a larger set of sellers need not mechanically compress prices and may instead increase the scope for relative price dispersion across stores (Varian, 1980; Lach, 2002; Kaplan, Menzio, Rudanko, and Trachter, 2019).

Assortment differentiation is also positively associated with dispersion, but along narrower margins. A one-standard-deviation increase in category entropy, 0.201, is associated with about 0.28 percentage points higher dispersion across markets and 0.10 percentage points higher dispersion within markets. The association becomes smaller and statistically insignificant within fixed product–market cells. Thus, assortment differentiation helps explain differences in dispersion across markets and within markets over time, but is less clearly associated with changes in dispersion for the same product in the same market.

Dispersion in store assortment size is associated with price dispersion mainly across markets. A one-standard-deviation increase in the standard deviation of product shares, 0.054, is associated with about 0.73 percentage points higher dispersion in the controlled across-market specification. The implied associations are not statistically significant within markets or within product–market cells. Thus, markets where stores differ more in their overall assortment size tend to have higher price dispersion, but changes in this variable within a market are not strongly associated with changes in dispersion.

The additional socioeconomic variables play a more limited role. Log real income is negatively associated with price dispersion in the across-market comparison, but not within markets or within product–market cells. Population density and unemployment are not systematically related to dispersion. Finally, the coefficient on the time trend remains positive and statistically significant in all specifications, indicating that observable market characteristics account for part, but not all, of the long-run increase in dispersion.

Online Appendix Section A reports additional specifications using lagged local market characteristics. Tables A.6 and A.7 use one-month and three-month lags of the microeconomic market characteristics and controls, while keeping the average price contemporaneous. The results are close to the contemporaneous estimates. Category entropy remains positive and statistically significant when comparing across markets for the same product and when comparing within markets over time. However, as in the contemporaneous specification, the coefficient becomes smaller and statistically insignificant when the comparison is made within the same product-market cell. This pattern holds for both one-month and three-month lags. Thus, assortment differentiation is persistently associated with dispersion across markets and within markets over time, but is less clearly related to changes in dispersion for a fixed product in a fixed market.

The remaining microeconomic variables also exhibit patterns similar to those in the contemporaneous results. Lagged log store competition is positive and statistically significant when the comparison is made within markets or within product-market cells, and it is also positive in the controlled across-market specifications. This reinforces the evidence that increases in local store competition are associated with higher price dispersion along within-market margins. By contrast, lagged dispersion in store assortment size is mainly associated with cross-market differences in dispersion: its coefficient is large and statistically significant in the across-market specifications, but becomes much smaller and statistically insignificant within markets and within product-market cells. Finally, the socioeconomic controls do not display a uniform pattern across margins.

Therefore, lagging local market characteristics does not change the main conclusion: observable market characteristics are associated with differences in price-dispersion levels, especially through local store competition, while price dispersion continues to increase over time along each margin of comparison.

We next examine whether the same local market characteristics are associated with the between-chain component of price dispersion. This exercise uses the between-chain database described above, in which prices are first collapsed to the chain–product–market–month level, and dispersion is then computed across chains within each product–market–month cell. Therefore, the dependent variable is not overall cross-store dispersion, but the component of dispersion that reflects price differences across seller units operating in the same local market, in which chains are collapsed to a single representative seller and independent stores remain as individual seller units.

The specifications follow the same structure as in Table 4. Columns (1) and (4) compare between-chain dispersion across markets and over time for the same product. Columns (2) and (5) use within-market variation over time. Columns (3) and (6) use changes within the same product–market cell over time. This allows us to assess whether the patterns documented for overall price dispersion are also present when the analysis focuses only on differences across chains. Because the between-chain and within-chain samples differ from the baseline sample, the economic magnitudes reported below for these components are computed using the standard deviation of each variable in the corresponding estimation sample.

Table 5 reports the results for between-chain price dispersion. The main result is that local store competition is the clearest correlate of dispersion across chains. The coefficient on *Log Store Competition* is positive and statistically significant in all specifications, and its magnitude is larger than in the aggregate table. With controls, the coefficient ranges from 0.9920 in the across-market comparison to about 2.1–2.2 in the within-market and product–market comparisons. Using the standard deviation of log store competition in the between-chain sample, 0.634, the within-market and product–market coefficients imply that a one-standard-deviation increase in competition is associated with about 1.34–1.38 additional percentage points of between-chain dispersion. Thus, markets with more

Table 5: Between-Chain Price Dispersion and Local Market Characteristics.

Dependent Variable:	SD (in %)					
	Without Controls			With Controls		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Av. Price	-9.655***	-9.324***	-7.992***	-9.284***	-9.130***	-7.865***
	(1.721)	(1.675)	(1.496)	(1.691)	(1.671)	(1.502)
Time	0.0164***	0.0161***	0.0163***	0.0165***	0.0164***	0.0167***
	(0.0024)	(0.0023)	(0.0022)	(0.0025)	(0.0026)	(0.0025)
Cat. Entropy	0.5260**	0.2147	0.0451	0.4831**	0.2484*	0.0563
	(0.2004)	(0.1291)	(0.1476)	(0.1821)	(0.1410)	(0.1622)
Log Store Competition	0.6218***	2.161***	2.208***	0.9920***	2.110***	2.183***
	(0.2206)	(0.4416)	(0.4240)	(0.2987)	(0.4317)	(0.4041)
SD Sh. Prod.	5.485*	0.6095	-0.3106	5.821**	0.5850	-0.5036
	(2.793)	(1.538)	(1.499)	(2.498)	(1.582)	(1.528)
Log Pop. Density				0.1239	4.014	3.473
				(0.2027)	(2.601)	(2.241)
Unemp. Rate				4.234**	5.063**	4.566**
				(1.995)	(1.940)	(1.888)
Log Real Income				-1.384***	-0.4258	-0.4941
				(0.3775)	(0.6146)	(0.6041)
Fixed-effects						
Product	Yes	Yes		Yes	Yes	
Market		Yes			Yes	
Product × Market			Yes			Yes
Fit statistics						
Observations	648,399	648,399	648,318	598,231	598,231	598,168
R^2	0.22531	0.24449	0.36912	0.23250	0.24742	0.36870
Within R^2	0.07459	0.06834	0.06621	0.08040	0.06938	0.06774

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

Notes: The dependent variable is between-chain price dispersion, computed across seller units within each product–market–month cell and multiplied by 100. Chain stores are collapsed into a single chain-level observation using the median price; independent stores are treated as individual seller units. *Av. Price* is the corresponding average log CPI-adjusted price. *Log Store Competition* is computed after collapsing chains and is defined as $\log(1 + N_{mt})$. Columns (1)–(3) exclude, and Columns (4)–(6) include unemployment, log real income, and log population density. Fixed effects are included as indicated. Regressions are weighted by the number of seller units used to compute dispersion. Standard errors are two-way clustered by product category and market.

competing sellers exhibit larger price differences across chains. This is in line with the relative-price-dispersion view of retail pricing, in which stores or chains may compete using different price vectors rather than a single common price (Kaplan, Menzio, Rudanko, and Trachter, 2019).

Assortment differentiation plays a more limited role in explaining levels of between-chain dispersion. Category entropy is positively associated with between-chain dispersion when comparing across markets for the same product, but the coefficient becomes smaller within markets and essentially disappears within product–market cells. This pattern is weaker than in the aggregate table, where category entropy is more clearly associated with overall dispersion across markets and within markets. Hence, assortment differentiation helps explain some differences in overall price dispersion, but it is less central than local store competition for explaining price differences across chains in fixed product–market cells.

Dispersion in store assortment size is also mainly associated with cross-market differences. Its coefficient is positive in the across-market comparison, but becomes small and statistically insignificant once market fixed effects or product-by-market fixed effects are included. This indicates that markets where stores differ more in their overall assortment size tend to display greater between-chain dispersion, but changes in this variable within the same market are not strongly associated with changes in between-chain dispersion.

The time trend remains large and statistically significant. With controls, the monthly trend is 0.0165 when comparing across markets for the same product, 0.0164 within markets, and 0.0167 within product–market cells. These estimates are larger than the corresponding coefficients in Table 4, which range from 0.0110 to 0.0119. Thus, even after accounting for observable market characteristics, between-chain dispersion continues to rise strongly over time.

Among the additional controls, unemployment is positively associated with between-chain dispersion in the specifications with controls. Log real income is negatively associated with between-chain dispersion only in the across-market comparison, whereas population density is not systematically related to it.

Overall, the comparison with Table 4 reinforces the section's main message: the clearest cross-sectional correlate of price dispersion is local store competition, and this association is especially strong across chains. At the same time, the persistent time trend confirms that the long-run increase in dispersion is mainly a between-chain phenomenon.

We next examine the within-chain component of price dispersion. The sample is restricted to chain stores, and dispersion is recalculated within each product–market–chain–month cell. The dependent variable, therefore, captures price differences across stores within the same chain for the same product, market, and month. The fixed-effect specifications are interpreted as in the previous tables, but now the relevant outcome is within-chain dispersion. Since stores of the same chain are part of the internal pricing structure being studied, *Log Store Competition* measures only external competition: the number of stores in the market and month that do not belong to the chain of the observation.

Table 6 reports the relationship between local market characteristics and within-chain price dispersion. It is worth keeping in mind that within-chain price dispersion is about one-seventh of between-chain dispersion. The dependent variable is now dispersion across stores belonging to the same chain, for the same product, market, and month. Therefore, the coefficients describe how internal price dispersion within retail chains varies with local market characteristics.

The most consistent result is that category-level assortment differentiation is positively associated with within-chain dispersion. Markets and periods in which stores differ more in the set of products offered within a category also display higher price dispersion across stores of the same chain. This pattern suggests that within-chain price differences are more closely related to product-assortment heterogeneity than to the number of external competitors the chain faces.

Using the standard deviation of category entropy in the within-chain sample, 0.108, the controlled product-by-market coefficient implies that a one-standard-deviation increase in assortment differentiation is associated with about a 0.11 percentage-point increase in within-chain dispersion. The association with dispersion in store assortment size is also economically relevant. Using the within-chain standard deviation of this variable, 0.018, the controlled across-market coefficient implies about a 0.27 percentage-point increase in within-chain dispersion per one standard deviation increase in store assortment

Table 6: Within-Chain Price Dispersion and Local Market Characteristics.

Dependent Variable:	SD (in %)					
	Without Controls			With Controls		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Av. Price	-1.896***	-1.524***	-1.441***	-1.701***	-1.506***	-1.408***
	(0.5470)	(0.4468)	(0.4394)	(0.5048)	(0.4461)	(0.4405)
Time	0.0010	0.0022	0.0023	0.0011	0.0021	0.0022
	(0.0013)	(0.0015)	(0.0015)	(0.0014)	(0.0016)	(0.0016)
Cat. Entropy	1.839***	0.9293***	1.019***	1.696***	0.9440***	1.035***
	(0.3005)	(0.2083)	(0.2265)	(0.2754)	(0.2176)	(0.2390)
Log Store Competition	-0.1752	-0.4762**	-0.4613**	0.1041	-0.4446*	-0.4406*
	(0.1059)	(0.2286)	(0.2227)	(0.1039)	(0.2327)	(0.2266)
SD Sh. Prod.	18.43***	7.042*	6.357	14.99***	6.809	6.187
	(4.266)	(4.067)	(4.199)	(4.580)	(4.294)	(4.404)
Log Pop. Density				-0.1731	-3.745	-3.283
				(0.1094)	(2.793)	(2.695)
Unemp. Rate				0.1996	-0.8807	-0.7613
				(1.341)	(1.202)	(1.131)
Log Real Income				-1.218***	-0.5567	-0.6135*
				(0.4094)	(0.3573)	(0.3400)
Fixed-effects						
Product	Yes	Yes		Yes	Yes	
Market		Yes			Yes	
Product × Market			Yes			Yes
Fit statistics						
Observations	513,346	513,346	513,319	490,852	490,852	490,825
R^2	0.07919	0.14001	0.23799	0.09540	0.14270	0.23989
Within R^2	0.04952	0.01457	0.01422	0.06496	0.01484	0.01442

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

Notes: The dependent variable is within-chain price dispersion, computed across stores belonging to the same chain within each product–market–chain–month cell and multiplied by 100. The sample is restricted to chain stores. *Av. Price* is the corresponding average log CPI-adjusted price. *Log Store Competition* measures external competition and is defined as $\log(1 + N^{out}_{smt})$, where N^{out}_{smt} is the number of stores in market m and month t that do not belong to chain s. Columns (1)–(3) exclude, and Columns (4)–(6) include unemployment, log real income, and log population density. Fixed effects are included as indicated. Regressions are weighted by the number of stores used to compute within-chain dispersion. Standard errors are two-way clustered by product category and market.

heterogeneity.

By contrast, external store competition plays a weaker role in the within-chain specifications. Unlike in the general and between-chain tables, the coefficient on *Log Store Competition* is not the dominant predictor of dispersion once the outcome is restricted to price differences across stores of the same chain. This is consistent with the interpretation that external competition matters primarily for price differences across chains, whereas internal chain dispersion is more closely tied to the heterogeneity of stores' product offerings.

The time trend is also much smaller in the within-chain specifications than in the overall and between-chain specifications. This is consistent with the earlier decomposition and with evidence that retail chains often use uniform or zone-pricing rules that limit price variation across stores within the same chain (DellaVigna and Gentzkow, 2019; Adams and Williams, 2019). The long-run increase in dispersion, therefore, appears to operate mainly across chains, rather than through increasing internal price heterogeneity within chains.

Taken together, the results show that aggregate price dispersion combines two distinct margins. The baseline estimates show a persistent increase in dispersion across all comparison margins: across markets for the same product, within markets over time, and within product–market cells. However, the chain decomposition shows that this increase is not mainly a within-chain phenomenon. It is concentrated in widening price differences across seller units, especially across retail chains.

The between-chain results point to local competitive structure as the main correlate of dispersion across chains. Store competition is strongly and positively associated with between-chain dispersion, indicating that markets with more competing seller units tend to display larger price differences across chains. Greater local competition therefore does not mechanically compress prices across chains; instead, it is associated with greater price differentiation among them.

The within-chain results show a different pattern. Once the comparison is restricted to stores belonging to the same chain, local competition is no longer the central correlate of dispersion. Assortment-related variables, especially category-level assortment differentiation and dispersion in store assortment size, are more closely associated with within-chain price differences. This suggests that internal price variation within chains is more closely related to heterogeneity in store assortments than to the number of outside competitors.

These within-chain associations should be interpreted with caution because the level of within-chain dispersion is very low. Average within-chain dispersion is about 0.96 percent, compared with 6.63 percent between chains; that is, within-chain dispersion is about one-seventh as large. Thus, even when assortment variables are statistically associated with within-chain dispersion, they operate on a much smaller margin than the between-chain component.

Overall, the section separates two margins that are mixed in the aggregate measure of price dispersion. Across chains, dispersion is mainly associated with local competitive structure and accounts for most of the long-run increase. Within chains, dispersion is much smaller and is more closely related to assortment heterogeneity. This distinction is central for interpreting price divergence: the increase in dispersion reflects mainly widening price differences across chains, not chains increasingly differentiating prices across their own stores.

5 Market Structure and the Speed of Price-Dispersion Growth

The previous section examined whether observable market characteristics are associated with differences in price dispersion levels. We now ask whether these same characteristics are associated with different speeds of price-dispersion growth over time.

This distinction is important because a market characteristic may be associated with higher dispersion in levels without being related to long-run divergence. For example, markets with more competing stores may display higher price dispersion at a point in time, but this does not imply that dispersion grows faster in those markets. Conversely, assortment differentiation may be less strongly associated with cross-sectional differences in dispersion, while being more closely related to changes in dispersion over time. We therefore interact the linear time trend with the microeconomic market characteristics studied above: category-level assortment differentiation, local store competition, and dispersion in store assortment size. The objective is to distinguish market characteristics associated with higher dispersion levels from those associated with faster growth in dispersion over time.

We extend Equation 2 to estimate specifications of the form:

$$SD_{imt} = \alpha + \beta \tilde{p}_{imt} + \gamma t + \theta' M_{mt} + \lambda' \widetilde{Z}_{imt} + \phi' \left(\widetilde{Z}_{imt} \times t \right) + \delta' FE_{imt} + \varepsilon_{imt}, \tag{3}$$

where $\tilde{p}_{imt}$ is the average log CPI-adjusted price in the product–market–month cell, t is a linear monthly time trend, and FE_{imt} denotes the same alternative sets of fixed effects used in Equation (1). The vector M_{mt} captures local socioeconomic and spatial conditions, while Z_{imt} captures microeconomic characteristics of the local retail environment, including assortment differentiation, store competition, and dispersion in store assortment size. We define

$$\widetilde{Z}_{imt} = Z_{imt} - \overline{Z},$$

where $\overline{Z}$ is the vector of sample means of the variables in Z_{imt}. Thus, the microeconomic characteristics enter the specification in deviations from their sample means, both as level terms and interacted with the linear time trend.

Because the specification includes interactions with the time trend, we focus the interpretation on the interaction coefficients ϕ. These coefficients indicate whether the time path of price dispersion differs systematically with microeconomic market structure. The coefficient γ measures the average monthly change in price dispersion when microeconomic market characteristics are at their sample means, while each element of ϕ measures how that trend changes when the corresponding characteristic is higher.

Table 7 examines whether microeconomic market characteristics are associated with different speeds of price-dispersion growth. Since the microeconomic variables are expressed as deviations from their sample means, the coefficient on *Time* measures the

Table 7: Price Dispersion and Local Market Characteristics: Interactions with Time.

Dependent Variable:	SD (in %)					
	Without Controls			With Controls		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Av. Price	-7.744***	-7.049***	-6.182***	-7.217***	-6.917***	-6.087***
	(1.500)	(1.405)	(1.237)	(1.444)	(1.403)	(1.242)
Time	0.0112***	0.0129***	0.0131***	0.0119***	0.0135***	0.0137***
	(0.0028)	(0.0025)	(0.0024)	(0.0028)	(0.0028)	(0.0027)
Cat. Entropy	0.4726	-0.6950**	-0.8855***	0.2571	-0.5702*	-0.8129**
	(0.4159)	(0.2962)	(0.3198)	(0.3896)	(0.3002)	(0.3317)
Log Store Competition	0.3885	2.003***	2.099***	0.8258***	1.917***	2.038***
	(0.2762)	(0.5435)	(0.5070)	(0.2906)	(0.5481)	(0.5118)
SD Sh. Prod.	20.56***	11.24**	9.282*	22.05***	11.74**	9.708*
	(5.650)	(5.451)	(5.258)	(4.134)	(5.611)	(5.409)
Time × Cat. Entropy	0.0101***	0.0101***	0.0098***	0.0096***	0.0092***	0.0094***
	(0.0026)	(0.0023)	(0.0023)	(0.0024)	(0.0023)	(0.0024)
Time × Log Store Competition	-0.0013	-0.0009	-0.0009	8.45×10^{-5}	-0.0006	-0.0007
	(0.0013)	(0.0017)	(0.0016)	(0.0013)	(0.0019)	(0.0017)
Time × SD Sh. Prod.	-0.0458	-0.0700*	-0.0636*	-0.0680**	-0.0736*	-0.0676*
	(0.0343)	(0.0366)	(0.0365)	(0.0335)	(0.0377)	(0.0376)
Log Pop. Density				-0.1134	2.416	1.952
				(0.2321)	(3.104)	(3.038)
Unemp. Rate				0.8476	2.539*	2.395*
				(2.282)	(1.399)	(1.398)
Log Real Income				-0.0001***	-4.74×10^{-5}	-4.61×10^{-5}
				(3.59×10^{-5})	(2.89×10^{-5})	(2.74×10^{-5})
Fixed-effects						
Product	Yes	Yes		Yes	Yes	
Market		Yes			Yes	
Product × Market			Yes			Yes
Fit statistics						
Observations	771,006	771,006	770,942	698,344	698,344	698,298
R^2	0.21119	0.26719	0.38234	0.22446	0.26527	0.37601
Within R^2	0.08904	0.05926	0.05914	0.09826	0.06008	0.06026

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

Notes: The dependent variable is price dispersion within product–market–month cells, measured as the cross-store standard deviation of log CPI-adjusted prices, multiplied by 100. Microeconomic market characteristics are entered as deviations from their sample means and interacted with *Time*. Columns (4)–(6) add unemployment, log real income, and log population density. Fixed effects are included as indicated. Regressions are weighted by the number of stores in each cell. Standard errors are two-way clustered by product category and market.

monthly trend in dispersion for observations with average values of these characteristics. The interaction terms show how this trend changes as each characteristic increases.

The clearest result concerns assortment differentiation. The interaction between *Time* and *Cat. Entropy* is positive, statistically significant, and similar across all margins of comparison. Using the standard deviation of category entropy reported in Table 1, 0.201, a one-standard-deviation increase in category entropy raises the monthly trend in price dispersion by about 0.00185–0.00203 percentage points. Over the 213-month sample period, this implies an additional increase of roughly 0.39–0.43 percentage points in price dispersion. Thus, markets with greater within-category assortment differentiation experience faster growth in price dispersion over time.

Log store competition shows a different pattern. The interaction between *Time* and *Log Store Competition* is small and statistically insignificant in all specifications. This indicates that, although store competition is associated with higher dispersion levels in the cross-sectional specifications, it is not systematically associated with faster growth in dispersion over time.

The interaction between *Time* and *SD Sh. Prod.* is negative in most specifications. This indicates that markets with greater heterogeneity in overall store assortment size do not experience faster dispersion growth; if anything, dispersion grows more slowly along this margin. Using the standard deviation of this variable in the regression sample, the controlled estimates imply that a one-standard-deviation increase in dispersion in store assortment size is associated with about 0.78–0.85 percentage points less cumulative growth in price dispersion over the sample period. Thus, markets with greater heterogeneity in overall store assortment size do not display faster long-run divergence; if anything, dispersion grows more slowly along this margin.

Overall, the table separates two margins. Store competition helps explain where price dispersion is higher, but it does not explain differences in the speed of dispersion growth. By contrast, within-category assortment differentiation is the microeconomic characteristic most clearly associated with faster long-run growth in price dispersion. This pattern is consistent with evidence that product variety and assortment choices affect price comparability across sellers and the measured deviations from price convergence (Borraz and Zipitría, 2022; Cavallo, Feenstra, and Inklaar, 2023).

We next examine whether local market characteristics are associated with different growth rates of between-chain price dispersion. Since the previous results show that the long-run increase in dispersion is concentrated between chains, this exercise helps identify which local characteristics are linked to faster divergence across chains. We therefore re-estimate the between-chain specifications, including interactions between the linear time trend and the three microeconomic market characteristics: category-level assortment differentiation, local store competition, and dispersion in store assortment size. The microeconomic variables are centered before interacting them with time, so the coefficient on the time trend measures the average trend for markets with average values of these characteristics.

Table 8 examines whether between-chain price dispersion grows at different speeds depending on local market characteristics. The columns again correspond to different margins of comparison. The main dynamic result is that assortment differentiation is systematically associated with faster growth in between-chain dispersion. The interaction between *Time* and *Cat. Entropy* is positive and statistically significant in all specifications. Using the standard deviation of category entropy in the between-chain sample, 0.356, the interaction coefficients imply that a one-standard-deviation increase in category entropy raises the cumulative growth of between-chain dispersion by about 0.45–0.50 percentage points over the sample period. Thus, markets with greater within-category assortment differentiation experience faster divergence across chains.

Log store competition displays a different pattern. The interaction between *Time* and *Log Store Competition* is small and statistically insignificant across specifications. This indicates that markets with more competing seller units do not experience systematically faster growth in between-chain dispersion over time.

Dispersion in store assortment size is also not associated with faster divergence between chains. The interaction between *Time* and *SD Sh. Prod.* is negative in all specifications and weakly statistically significant in the within-market and product–market specifications. Thus, markets with greater heterogeneity in overall store assortment size

Table 8: Between-Chain Price Dispersion and Local Market Characteristics: Interactions with Time.

Dependent Variable:	SD (in %)					
	Without Controls			With Controls		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Av. Price	-9.604***	-9.257***	-7.939***	-9.203***	-9.051***	-7.799***
	(1.710)	(1.664)	(1.487)	(1.679)	(1.660)	(1.491)
Time	0.0176***	0.0169***	0.0166***	0.0170***	0.0180***	0.0175***
	(0.0027)	(0.0025)	(0.0024)	(0.0028)	(0.0028)	(0.0027)
Cat. Entropy	-0.3016	-0.5628*	-0.7129**	-0.3036	-0.4388	-0.6623*
	(0.3424)	(0.3115)	(0.3348)	(0.3242)	(0.3155)	(0.3389)
Log Store Competition	0.9274***	2.138***	2.062***	1.005***	2.100***	2.054***
	(0.2705)	(0.5016)	(0.4483)	(0.3465)	(0.4928)	(0.4369)
SD Sh. Prod.	7.907*	7.848**	6.717*	11.35***	8.219*	7.069*
	(4.367)	(3.876)	(3.851)	(3.400)	(4.137)	(4.039)
Time × Cat. Entropy	0.0072**	0.0067**	0.0066**	0.0067**	0.0059**	0.0062**
	(0.0027)	(0.0026)	(0.0026)	(0.0027)	(0.0025)	(0.0026)
Time × Log Store Competition	-0.0026	0.0004	0.0013	3.96×10^{-6}	0.0002	0.0012
	(0.0020)	(0.0015)	(0.0014)	(0.0019)	(0.0018)	(0.0016)
Time × SD Sh. Prod.	-0.0198	-0.0585**	-0.0568**	-0.0451	-0.0622**	-0.0613**
	(0.0292)	(0.0288)	(0.0279)	(0.0297)	(0.0299)	(0.0288)
Log Pop. Density				0.0819	4.319	3.449
				(0.1861)	(2.886)	(2.466)
Unemp. Rate				4.658**	4.765***	4.471***
				(1.838)	(1.622)	(1.628)
Log Real Income				-8.89×10^{-5}***	-4.98×10^{-5}	-4.55×10^{-5}
				(2.1×10^{-5})	(3.32×10^{-5})	(3.19×10^{-5})
Fixed-effects						
Product	Yes	Yes		Yes	Yes	
Market		Yes			Yes	
Product × Market			Yes			Yes
Fit statistics						
Observations	648,399	648,399	648,318	598,231	598,231	598,168
R^2	0.22582	0.24512	0.36964	0.23310	0.24814	0.36932
Within R^2	0.07519	0.06911	0.06697	0.08112	0.07027	0.06865

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

Notes: The dependent variable is between-chain price dispersion, measured as the standard deviation of log CPI-adjusted prices across seller units within each product–market–month cell, multiplied by 100. Chain stores are collapsed into a single chain-level seller using the median price; independent stores enter as individual seller units. Microeconomic market characteristics are entered as deviations from their sample means and interacted with *Time*. *Log Store Competition* is $\log(1 + N_{mt})$, where N_{mt} is the number of competing seller units after collapsing chain stores. Columns (1)–(3) exclude, and Columns (4)–(6) include unemployment, log real income, and log population density. Fixed effects are included as indicated. Regressions are weighted by the number of seller units used to compute dispersion. Standard errors are two-way clustered by product category and market.

do not display faster growth in between-chain dispersion; if anything, dispersion grows more slowly along this margin.

Overall, the table shows that the dynamic association is concentrated in category-level assortment differentiation. The results are very similar with and without socioeconomic controls, indicating that the estimated differences in trend are not driven by the inclusion of income, unemployment, or population density.

We then repeat the interaction exercise for within-chain dispersion, asking whether internal price dispersion within chains grows faster in markets with different local characteristics. The unit of observation is now the product–chain–market–month cell, and the dependent variable measures price dispersion across stores belonging to the same chain. As before, the microeconomic variables are centered before being interacted with the linear time trend, so the coefficient on *Time* measures the trend for observations with average values of these characteristics.

Table 9 examines whether within-chain price dispersion grows at different speeds depending on local market characteristics. The first result is that there is no systematic upward trend in within-chain dispersion: the coefficient on *Time* is small and statistically insignificant in every specification. This is consistent with the earlier decomposition and with evidence that centralized chain pricing limits store-level price variation (DellaVigna and Gentzkow, 2019; Adams and Williams, 2019; Daruich and Kozlowski, 2023).

The interaction terms show little evidence that local market characteristics predict faster growth in within-chain dispersion. The interaction between *Time* and *Cat. Entropy* is small and statistically insignificant throughout the table, unlike the positive dynamic association found for aggregate and between-chain dispersion. The interaction between *Time* and *Log Store Competition* is also not systematically significant, indicating that external competitive pressure is not associated with faster internal price divergence within chains.

The only partial exception is *SD Sh. Prod.*: its interaction with *Time* is negative in all specifications, but statistically significant mainly in the across-market specifications.

Table 9: Within-Chain Price Dispersion and Local Market Characteristics: Interactions with Time.

Dependent Variable:	SD (in %)					
	Without Controls			With Controls		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Av. Price	-1.898***	-1.511***	-1.430***	-1.695***	-1.506***	-1.411***
	(0.5359)	(0.4360)	(0.4276)	(0.4920)	(0.4405)	(0.4345)
Time	0.0022	0.0026	0.0026	0.0022	0.0021	0.0023
	(0.0014)	(0.0016)	(0.0016)	(0.0015)	(0.0020)	(0.0020)
Cat. Entropy	1.556***	0.6943	0.8775**	1.467***	0.7072	0.8787**
	(0.4910)	(0.4159)	(0.4010)	(0.4346)	(0.4349)	(0.4227)
Log Store Competition	0.0256	-0.3051	-0.3067	0.2832*	-0.4089*	-0.4032*
	(0.1533)	(0.1985)	(0.1992)	(0.1443)	(0.2027)	(0.2010)
SD Sh. Prod.	34.38***	10.89**	9.968*	30.04***	11.67**	10.65**
	(6.769)	(4.928)	(5.006)	(7.642)	(4.767)	(4.893)
Time × Cat. Entropy	0.0019	0.0021	0.0012	0.0012	0.0021	0.0013
	(0.0037)	(0.0033)	(0.0029)	(0.0033)	(0.0033)	(0.0030)
Time × Log Store Competition	-0.0015*	-0.0010	-0.0009	-0.0012	-0.0002	-0.0002
	(0.0009)	(0.0009)	(0.0008)	(0.0009)	(0.0011)	(0.0010)
Time × SD Sh. Prod.	-0.1265***	-0.0288	-0.0269	-0.1221***	-0.0373	-0.0341
	(0.0389)	(0.0339)	(0.0337)	(0.0409)	(0.0341)	(0.0337)
Log Pop. Density				-0.2229*	-3.529	-2.991
				(0.1117)	(3.215)	(3.102)
Unemp. Rate				0.0384	-0.8330	-0.6796
				(1.518)	(1.156)	(1.087)
Log Real Income				-7.82×10^{-5}***	-2.9×10^{-5}	-2.93×10^{-5}
				(1.87×10^{-5})	(1.85×10^{-5})	(1.77×10^{-5})
Fixed-effects						
Product	Yes	Yes		Yes	Yes	
Market		Yes			Yes	
Product × Market			Yes			Yes
Fit statistics						
Observations	513,346	513,346	513,319	490,852	490,852	490,825
R^2	0.08149	0.14033	0.23823	0.09864	0.14279	0.23990
Within R^2	0.05189	0.01494	0.01453	0.06831	0.01495	0.01444

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

Notes: The dependent variable is within-chain price dispersion, measured as the standard deviation of log CPI-adjusted prices across stores belonging to the same chain within each product–chain–market–month cell, multiplied by 100. Microeconomic market characteristics are entered as deviations from their sample means and interacted with *Time*. *Log Store Competition* is computed at the chain–market–month level and measures competing stores outside the chain. Columns (1)–(3) exclude, and Columns (4)–(6) include unemployment, log real income, and log population density. Fixed effects are included as indicated. Regressions are weighted by the number of stores used to compute each dispersion measure. Standard errors are two-way clustered by product category and market.

Using the standard deviation of *SD Sh. Prod.* in the within-chain sample, 0.018, the coefficient in Column (4) implies about 0.47 percentage points less cumulative growth in within-chain dispersion over the sample period.[4] Since this pattern does not hold within markets or within product–market cells, it should be read mainly as a cross-market association.

Overall, the table reinforces the distinction between between-chain and within-chain dispersion. The long-run increase in price dispersion operates primarily across chains. Within-chain dispersion is low, shows no upward trend, and does not appear to grow faster in markets with greater assortment differentiation or stronger external competition.

Taken together, the interaction results show that microeconomic market characteristics are associated with different speeds of price-dispersion growth. The key dynamic correlate is category-level assortment differentiation. In the aggregate and between-chain specifications, markets with greater within-category assortment differentiation experience faster growth in price dispersion over time. This pattern is robust across margins of comparison and remains similar after adding socioeconomic controls.

By contrast, local store competition is not systematically associated with faster dispersion growth. This is important because store competition is one of the strongest correlates of dispersion levels in the previous section, especially for aggregate and between-chain dispersion. The interaction results show that this association is mainly about where dispersion is higher, not where dispersion grows faster. Dispersion in store assortment size also does not predict faster divergence; if anything, its interaction with time is negative in several specifications.

The chain decomposition further sharpens the interpretation. The dynamic association between assortment differentiation and dispersion growth appears in the aggregate and between-chain results, but not within chains. Within-chain dispersion remains low, displays no systematic upward trend, and does not grow faster in markets with stronger external competition or greater category-level assortment differentiation. Thus, the long-

[4] The calculation is $-0.1221 \times 0.0183 \times 212 = -0.47$ percentage points.

run divergence documented in the paper is not driven by chains increasingly differentiating prices across their own stores. It is primarily a between-chain phenomenon, and its speed is greater in markets where chains are more differentiated in the products they offer.

Overall, this section shows that observable microeconomic characteristics of retail markets are not merely correlated with dispersion levels. They are also related to the pace at which dispersion evolves. Local competition helps explain where price dispersion is higher, while assortment differentiation helps explain where price dispersion grows faster. This distinction is central to the paper's interpretation: long-run price divergence reflects the interaction between chain-level pricing and the evolution of product differentiation across local retail markets.

6 Conclusion

This paper studies the long-run evolution of retail price dispersion using detailed store-level supermarket price data from Montevideo, Uruguay. The first result is that price dispersion increases persistently over time. The increase is large relative to the initial level of dispersion and appears across all margins of comparison: across markets for the same product, within markets over time, and within product–market cells. Thus, long-run divergence is not an artifact of a particular specification or comparison margin.

The second result is that this divergence is mainly a between-chain phenomenon. Between-chain dispersion rises substantially over the sample period, while within-chain dispersion remains low and shows no comparable upward trend. Retail chains therefore appear to maintain relatively compressed internal pricing structures, but price differences across chains widen over time. The long-run increase in local price dispersion is not driven by chains increasingly differentiating prices across their own stores; it is driven by widening differences across chains and independent seller units.

The third result concerns cross-sectional differences in dispersion. Local store competition is the strongest correlate of dispersion levels, especially in the aggregate and between-chain specifications. Markets with more competing sellers exhibit larger price differences among sellers. This indicates that a larger number of local competitors does not mechanically imply price convergence; in these retail markets, competition is associated with greater relative price dispersion across seller units.

The fourth result concerns dispersion dynamics. The variables that explain where dispersion is higher are not necessarily the variables that explain where dispersion grows faster. Local store competition is not systematically associated with faster dispersion growth. Instead, within-category assortment differentiation is the microeconomic characteristic most closely associated with different speeds of price-dispersion growth. Markets with greater assortment differentiation experience faster growth in aggregate and between-chain dispersion over time.

Taken together, the findings show that long-run price divergence is a structured retail-market phenomenon. Dispersion rises broadly, but its main source is between chains. Competition helps explain dispersion levels, while assortment differentiation helps explain dispersion dynamics. This distinction matters because it links persistent price divergence to the organization of retail markets: prices are shaped not only by how many sellers operate locally, but also by how chains differentiate their assortments, store formats, and pricing strategies.

The results matter beyond the Uruguayan setting because retail chains are central actors in consumer markets worldwide. When pricing decisions are organized at the chain level, local price integration depends not only on the number of stores selling the same product, but also on how chains differentiate prices and assortments across local markets. A natural next step is to combine these price data with quantities or household-level shopping behavior to distinguish more directly among search-, assortment-, and demand-based mechanisms. Our evidence documents where long-run divergence occurs and which market characteristics are associated with it; identifying the structural contribution of each mechanism remains an important task for future work.

Declaration of Generative AI and AI-Assisted Technologies

During the preparation of this manuscript, the authors used OpenAI's ChatGPT as an auxiliary tool to support manuscript drafting and editing, LaTeX formatting, R code development and debugging, table and figure preparation, and consistency checks across sections. The tool was also used to help improve the clarity and organization of the exposition. The authors did not use generative AI to create, alter, or manipulate the underlying data, empirical results, or statistical estimates. All AI-assisted outputs were reviewed, edited, and verified by the authors, who take full responsibility for the content of the manuscript.

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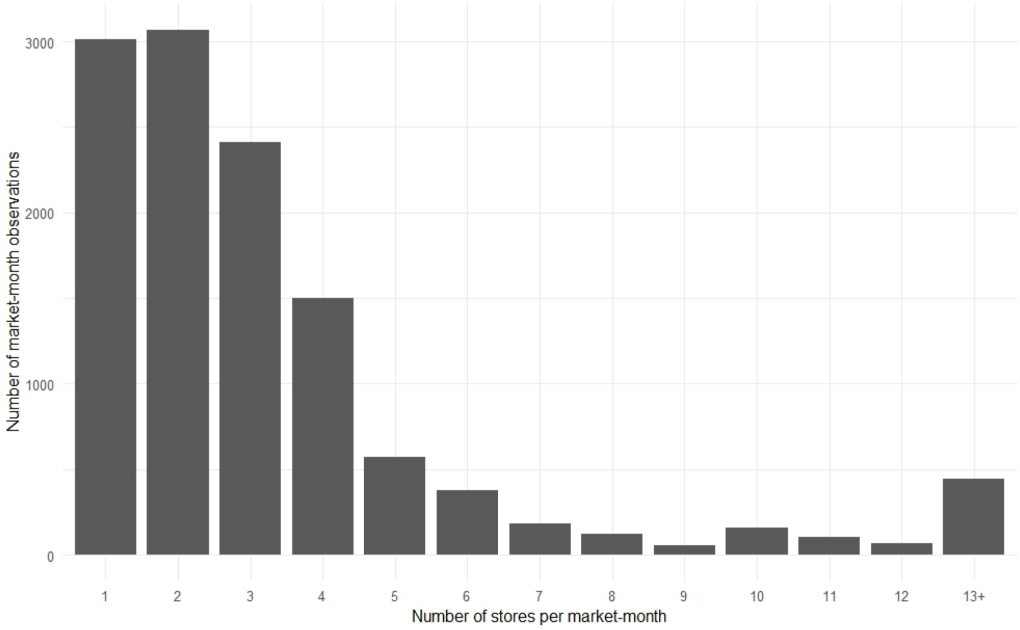
Online Appendix A. Additional Tables and Figures

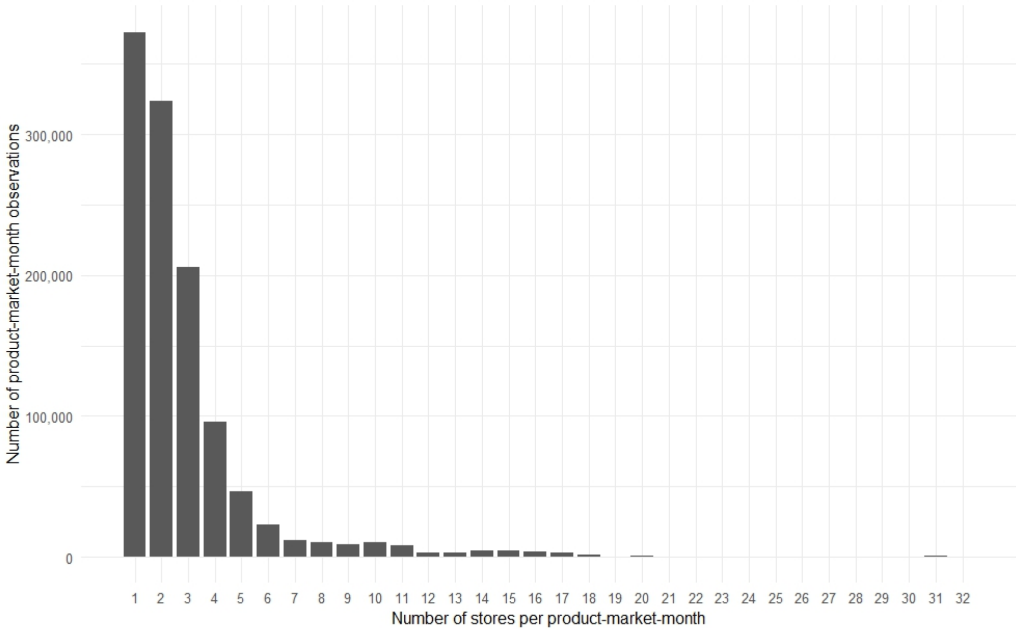
A.1 Sample Coverage

Figure A.1: Distribution of Stores per Market-Month.



Notes: The figure shows the distribution of the number of active stores in each market-month over the full sample. Store counts are computed after collapsing the data to one observation per store–market–month, so each store is counted once in a given market and month, regardless of the number of products observed. The last bin groups market-month observations with 13 or more stores.

Figure A.2: Distribution of Stores per Product–Market–Month.



Notes: The figure shows the distribution of the number of stores observed in each product–market–month cell over the full sample. Store counts are computed after collapsing the data to one observation per product–store–market–month, so each store is counted once for a given product, market, and month.

A.2 Baseline Trend Robustness

Table A.1: Baseline Price-Dispersion Trend Estimates: Quadratic Trend.

Dependent Variable:	SD (in %)					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Constant	11.10***					
	(1.684)					
Av. Price	-2.103***	-7.388***	-6.896***	-6.885***	-6.025***	-6.012***
	(0.4899)	(1.509)	(1.432)	(1.433)	(1.264)	(1.265)
Time	0.0162***	0.0163***	0.0166***	0.0166***	0.0165***	0.0165***
	(0.0022)	(0.0022)	(0.0020)	(0.0020)	(0.0020)	(0.0020)
$(Time - \overline{Time})^2$/10,000	-0.1891	0.1614	0.1983	0.2015	0.2014	0.2053
	(0.3864)	(0.3710)	(0.3540)	(0.3545)	(0.3484)	(0.3489)
Fixed-effects						
Product		Yes	Yes	Yes		
Market			Yes	Yes		
Month				Yes		Yes
Product × Market					Yes	Yes
Fit statistics						
Observations	771,006	771,006	771,006	771,006	770,942	770,942
R^2	0.05774	0.17631	0.26032	0.26059	0.37662	0.37689
Within R^2		0.04877	0.05044	0.05042	0.05044	0.05043

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

Notes: The dependent variable is the cross-store standard deviation of log CPI-adjusted prices within each product-market-month cell, multiplied by 100. *Av. Price* is the corresponding cross-store average log price, and *Time* is a linear monthly trend. The quadratic term is constructed as the squared deviation of *Time* from its sample mean and divided by 10,000. Product, market, month, and product-by-market fixed effects are included as indicated. Regressions are weighted by the number of stores in each cell. Standard errors are two-way clustered by product category and market.

Table A.2: Average Price Trend Estimation.

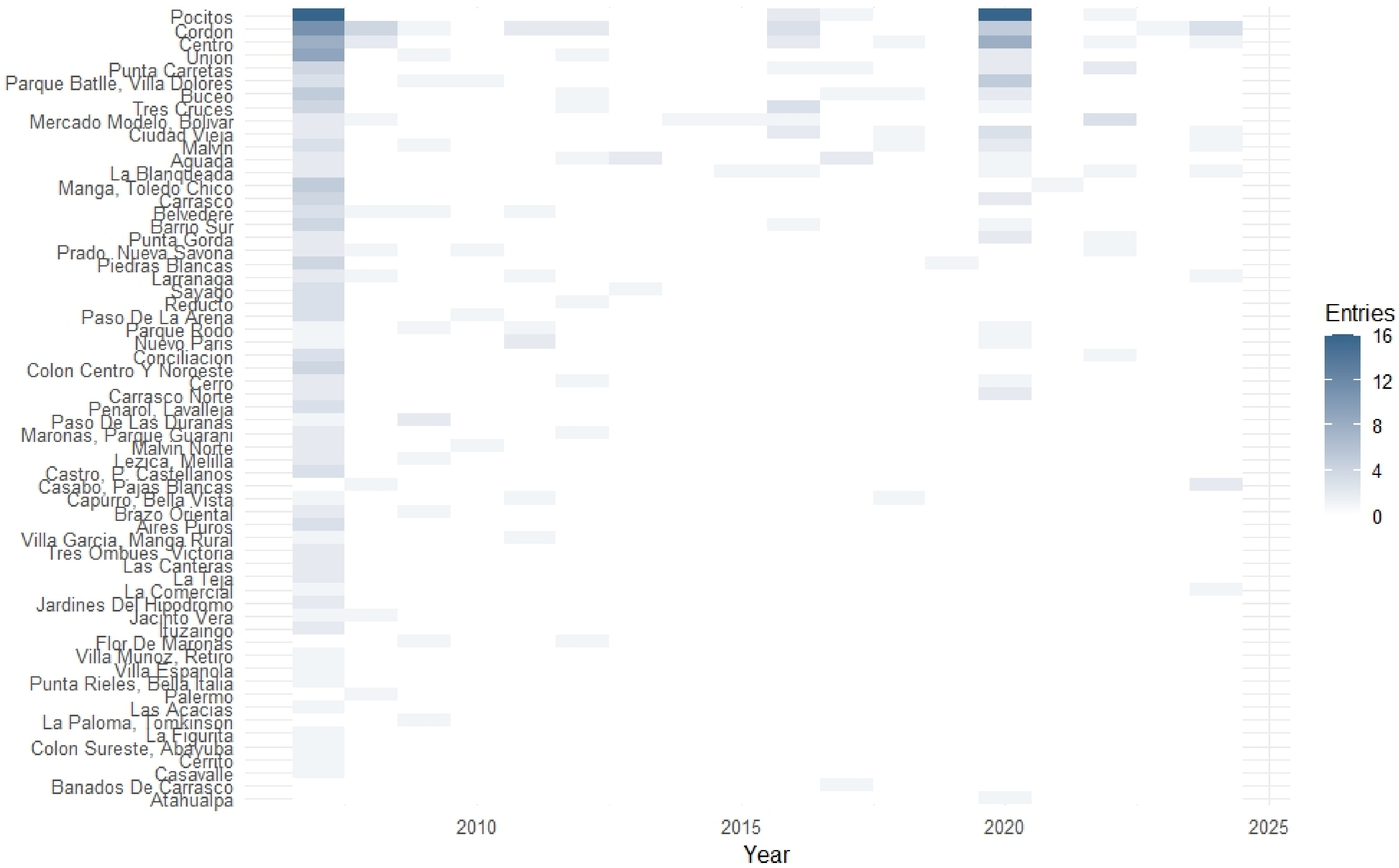
Dependent Variable:	Av. Price					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Constant	3.279^{***}					
	(0.0854)					
Time	3.21×10^{-5}	8.53×10^{-5}	8.3×10^{-5}	8.12×10^{-5}	8.44×10^{-5}	8.26×10^{-5}
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Fixed-effects						
Product		Yes	Yes	Yes		
Market			Yes	Yes		
Month				Yes		Yes
Product $\times$ Market					Yes	Yes
Fit statistics						
Observations	1,143,448	1,143,448	1,143,448	1,143,448	1,143,392	1,143,392
R^2	1.21×10^{-5}	0.94355	0.94429	0.94434	0.94883	0.94888
Within R^2		0.00142	0.00133	0.00127	0.00147	0.00141

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

Notes: The dependent variable is the cross-store average of log CPI-adjusted prices within each product-market-month cell. *Time* is a linear monthly trend. Product, market, month, and product-by-market fixed effects are included as indicated. Regressions are weighted by the number of stores in each cell. Standard errors are two-way clustered by product category and market.

A.3 Store Entry and Sample Composition

Figure A.3: Store Entry Across Neighborhoods Over Time.



Notes: The figure reports the number of stores first observed in each neighborhood and year. Store entry is computed after collapsing the data to the store–neighborhood–month level. The first year of the sample captures the initial stock of observed stores rather than true entry. Darker cells indicate more stores first observed in a given neighborhood-year.

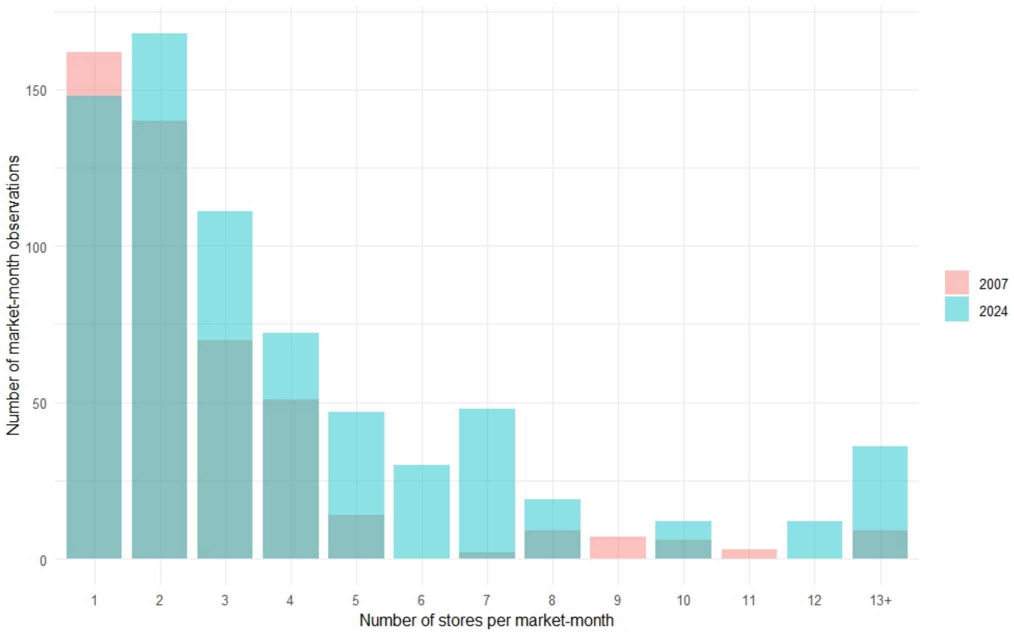
Table A.3: Baseline Price-Dispersion Trend Estimates: Initial Sample Stores.

Dependent Variable:	SD (in %)					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Constant	10.05***					
	(1.466)					
Av. Price	-1.907***	-8.243***	-7.766***	-7.763***	-6.711***	-6.707***
	(0.4510)	(1.530)	(1.428)	(1.431)	(1.250)	(1.253)
Time	0.0132***	0.0129***	0.0129***	0.0129***	0.0129***	0.0129***
	(0.0026)	(0.0026)	(0.0024)	(0.0024)	(0.0024)	(0.0024)
Fixed-effects						
Product		Yes	Yes	Yes		
Market			Yes	Yes		
Month				Yes		Yes
Product × Market					Yes	Yes
Fit statistics						
Observations	623,312	623,312	623,312	623,312	623,222	623,222
R^2	0.04156	0.14610	0.22892	0.22915	0.35825	0.35847
Within R^2		0.04582	0.04589	0.04589	0.04321	0.04321

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

Notes: The dependent variable is the cross-store standard deviation of log CPI-adjusted prices within each product-market-month cell, multiplied by 100. The sample is restricted to stores that were already present in 2007. *Av. Price* is the corresponding cross-store average log price, and *Time* is a linear monthly trend. Product, market, month, and product-by-market fixed effects are included as indicated. Regressions are weighted by the number of stores in each cell. Standard errors are two-way clustered by product category and market.

Figure A.4: Distribution of Stores per Market-Month: 2007 versus 2024.



Notes: The figure shows overlapping distributions of the number of active stores in each market-month for 2007 and 2024. Store counts are computed after collapsing the data to one observation per store–market–month, so each store is counted once in a given market and month, regardless of the number of products observed. The last bin groups market-month observations with 13 or more stores.

Table A.4: Baseline Price-Dispersion Trend Estimates: Excluding High-Entry Markets.

Dependent Variable:	SD (in %)					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Constant	11.05***					
	(1.742)					
Av. Price	-2.194***	-8.448***	-7.731***	-7.725***	-6.649***	-6.641***
	(0.5063)	(1.629)	(1.529)	(1.531)	(1.323)	(1.325)
Time	0.0164***	0.0160***	0.0168***	0.0168***	0.0167***	0.0167***
	(0.0026)	(0.0026)	(0.0023)	(0.0023)	(0.0022)	(0.0022)
Fixed-effects						
Product		Yes	Yes	Yes		
Market			Yes	Yes		
Month				Yes		Yes
Product × Market					Yes	Yes
Fit statistics						
Observations	617,916	617,916	617,916	617,916	617,859	617,859
R^2	0.05517	0.16490	0.26171	0.26187	0.39532	0.39547
Within R^2		0.05077	0.05257	0.05256	0.05134	0.05132

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

Notes: The dependent variable is the cross-store standard deviation of log CPI-adjusted prices within each product–market–month cell, multiplied by 100. *Av. Price* is the corresponding cross-store average log price, and *Time* is a linear monthly trend. The sample excludes high-entry markets, defined as markets in the top decile of total store entries after the initial sample year. Stores first observed in 2007 are treated as part of the initial stock rather than as entrants. Product, market, month, and product-by-market fixed effects are included as indicated. Regressions are weighted by the number of stores in each cell. Standard errors are two-way clustered by product category and market.

Table A.5: Baseline Price-Dispersion Trend Estimates: Excluding High-Entry Markets, 2011 Onward.

Dependent Variable:	SD (in %)					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Constant	11.78***					
	(1.842)					
Av. Price	-2.409***	-9.863***	-8.956***	-8.948***	-7.652***	-7.641***
	(0.5377)	(1.992)	(1.887)	(1.890)	(1.674)	(1.677)
Time	0.0163***	0.0170***	0.0179***	0.0179***	0.0179***	0.0180***
	(0.0030)	(0.0032)	(0.0028)	(0.0028)	(0.0027)	(0.0028)
Fixed-effects						
Product		Yes	Yes	Yes		
Market			Yes	Yes		
Month				Yes		Yes
Product × Market					Yes	Yes
Fit statistics						
Observations	530,444	530,444	530,444	530,444	530,390	530,390
R^2	0.05201	0.17066	0.26832	0.26848	0.41714	0.41730
Within R^2		0.05350	0.05367	0.05359	0.05169	0.05161

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

Notes: The dependent variable is the cross-store standard deviation of log CPI-adjusted prices within each product–market–month cell, multiplied by 100. *Av. Price* is the corresponding cross-store average log price, and *Time* is a linear monthly trend. The sample is restricted to observations from 2011 onward and excludes high-entry markets, defined as markets in the top decile of total store entries after the initial sample year. Stores first observed in 2007 are treated as part of the initial stock rather than as entrants. Product, market, month, and product-by-market fixed effects are included as indicated. Regressions are weighted by the number of stores in each cell. Standard errors are two-way clustered by product category and market.

A.4 Lagged Local Market Characteristics

Table A.6: Price Dispersion and Lagged Local Market Characteristics: One-Month Lag.

Dependent Variable:	SD (in %)					
	Without Controls			With Controls		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Av. Price	-7.882***	-7.172***	-6.260***	-7.433***	-7.055***	-6.181***
	(1.531)	(1.435)	(1.261)	(1.479)	(1.434)	(1.268)
Time	0.0103***	0.0124***	0.0127***	0.0113***	0.0126***	0.0129***
	(0.0025)	(0.0023)	(0.0022)	(0.0026)	(0.0025)	(0.0024)
Cat. Entropy$_{t-1}$	1.671***	0.5259***	0.2873	1.427***	0.5461***	0.3034
	(0.3494)	(0.1738)	(0.1740)	(0.3414)	(0.1821)	(0.1850)
Log Store Comp.$_{t-1}$	0.2114	1.409***	1.515***	0.7599***	1.405***	1.523***
	(0.1987)	(0.3748)	(0.3619)	(0.2557)	(0.3661)	(0.3476)
SD Sh. Prod.$_{t-1}$	14.32***	2.269	1.115	12.86***	2.307	1.002
	(3.774)	(2.289)	(2.155)	(3.376)	(2.397)	(2.246)
Log Pop. Density$_{t-1}$				-0.0401	2.609	2.173
				(0.2592)	(2.577)	(2.537)
Unemp. Rate$_{t-1}$				0.9232	3.068	2.827
				(2.593)	(1.826)	(1.725)
Log Income$_{t-1}$				-1.823***	-0.4040	-0.4877
				(0.6189)	(0.5833)	(0.5643)
Fixed-effects						
Product	Yes	Yes		Yes	Yes	
Market		Yes			Yes	
Product × Market			Yes			Yes
Fit statistics						
Observations	763,869	763,869	763,816	692,737	692,737	692,702
R^2	0.20984	0.26521	0.38107	0.22153	0.26345	0.37496
Within R^2	0.08647	0.05677	0.05640	0.09402	0.05749	0.05742

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

Notes: The dependent variable is the cross-store standard deviation of log CPI-adjusted prices within each product–market–month cell, multiplied by 100. *Av. Price* is the contemporaneous cross-store average log CPI-adjusted price, and *Time* is a linear monthly trend. Local market characteristics and controls are lagged one month, as indicated by the subscript $t-1$. Columns (1)–(3) include only lagged microeconomic market characteristics, while Columns (4)–(6) add lagged unemployment, log income, and log population density. Product, market, and product-by-market fixed effects are included as indicated. Regressions are weighted by the number of stores in each product–market–month cell. Standard errors are two-way clustered by product category and market.

Table A.7: Price Dispersion and Lagged Local Market Characteristics: Three-Month Lag.

Dependent Variable:	SD (in %)					
	Without Controls			With Controls		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Av. Price	-7.936***	-7.216***	-6.283***	-7.508***	-7.106***	-6.213***
	(1.548)	(1.450)	(1.274)	(1.495)	(1.449)	(1.282)
Time	0.0105***	0.0128***	0.0131***	0.0116***	0.0130***	0.0134***
	(0.0025)	(0.0022)	(0.0022)	(0.0026)	(0.0024)	(0.0024)
Cat. Entropy$_{t-3}$	1.633***	0.4926***	0.2369	1.392***	0.5159***	0.2558
	(0.3466)	(0.1677)	(0.1682)	(0.3386)	(0.1749)	(0.1780)
Log Store Comp.$_{t-3}$	0.2144	1.339***	1.438***	0.7541***	1.332***	1.442***
	(0.1962)	(0.3597)	(0.3474)	(0.2546)	(0.3457)	(0.3280)
SD Sh. Prod.$_{t-3}$	14.17***	2.122	1.012	12.50***	2.143	0.8882
	(3.758)	(2.210)	(2.073)	(3.367)	(2.334)	(2.182)
Log Pop. Density$_{t-3}$				-0.0379	2.709	2.282
				(0.2608)	(2.529)	(2.486)
Unemp. Rate$_{t-3}$				1.493	3.592**	3.253*
				(2.508)	(1.738)	(1.631)
Log Income$_{t-3}$				-1.771***	-0.4459	-0.5163
				(0.6135)	(0.6027)	(0.5880)
Fixed-effects						
Product	Yes	Yes		Yes	Yes	
Market		Yes			Yes	
Product × Market			Yes			Yes
Fit statistics						
Observations	753,680	753,680	753,626	683,200	683,200	683,164
R^2	0.21072	0.26570	0.38268	0.22212	0.26399	0.37658
Within R^2	0.08621	0.05657	0.05619	0.09333	0.05740	0.05729

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

Notes: The dependent variable is the cross-store standard deviation of log CPI-adjusted prices within each product–market–month cell, multiplied by 100. *Av. Price* is the contemporaneous cross-store average log CPI-adjusted price, and *Time* is a linear monthly trend. Local market characteristics and controls are lagged three months, as indicated by the subscript $t-3$. Columns (1)–(3) include only lagged microeconomic market characteristics, while Columns (4)–(6) add lagged unemployment, log real income, and log population density. Product, market, and product-by-market fixed effects are included as indicated. Regressions are weighted by the number of stores in each product–market–month cell. Standard errors are two-way clustered by product category and market.

Online Appendix B. Construction of Neighborhood Socioeconomic Controls

First, we construct neighborhood income using household survey information from INE (*Instituto Nacional de Estadística).* Income is measured net of taxes, consistent with the definition used in the household survey, and captures the disposable income available to households for consumption. Unemployment is computed as the weighted number of people who declared being unemployed. The procedure below is for income, but is the same for unemployment.

For each neighborhood, monthly income is computed as a six-month rolling average of current and lagged income. Let y_{it} denote the resulting six-month average income for neighborhood i in month t:

$$y_{it} = \frac{1}{6} \sum_{s=t-5}^{t} y_{is}^{raw},$$

where y_{is}^{raw} is the average income observed in neighborhood i in month s. This rolling average is computed prior to the outlier detection and interpolation steps described below.

Because some neighborhood-month cells have missing values or display sharp fluctuations due to limited household observations, we apply a cleaning procedure to the resulting monthly neighborhood income series. Let i index neighborhoods and t months. The variable of interest is neighborhood mean income, denoted by $income_{it}$. All computations are performed after sorting the data by neighborhood and month.

The procedure consists of two steps: (i) identification and treatment of outliers, and (ii) interpolation of missing values.

Outlier detection

Outliers were identified using within-neighborhood monthly changes in log income. For each neighborhood i, we computed

$$\Delta \log(y_{it}) = \log(y_{it}) - \log(y_{i,t-1}). \tag{4}$$

We then calculated the neighborhood-specific median absolute deviation (MAD) of this monthly change series,

$$MAD_i\Big(\Delta \log(y_{it}\Big) = \text{median}_t \left(\Big|\Delta \log(y_{it}) - \text{median}_t\Big(\Delta \log(y_{it})\Big)\Big|\right). \tag{5}$$

An observation was classified as a soft outlier if its absolute monthly change exceeded the larger of a fixed threshold and three times the neighborhood-specific MAD:

$$|\Delta \log(y_{it})| > \max\Big\{0.10,\ 3 \times MAD_i\Big(\Delta \log(y)\Big)\Big\}. \tag{6}$$

An observation was classified as a hard outlier if

$$|\Delta \log(y_{it})| > 0.20. \tag{7}$$

In the cleaning stage, hard outliers were recoded as missing values prior to interpolation. In addition, zero values were also treated as missing.

Interpolation

After removing hard outliers and recoding zeros as missing values, the income series was completed in three steps.

First, we constructed a balanced neighborhood-month panel by generating the full sequence of months for each neighborhood. This ensured that all missing months were explicitly represented.

Second, gaps of one or two consecutive months were filled by linear interpolation in logarithms. Let $\mathcal{I}[\cdot]$ denote linear interpolation across adjacent non-missing observations. For short gaps, imputed income was defined as

$$\widetilde{y}_{it} = \exp\left(\mathcal{I}\Big[\log(y_{it})\Big]\right). \tag{8}$$

Third, any remaining missing observations were imputed using Kalman smoothing based on a univariate structural time-series model estimated separately for each neighborhood. The model was applied to the log income series and used to recover values not filled by short-gap interpolation.

As a final fallback, residual missing observations were imputed using the cross-sectional structure of the city. For each month t, we computed the citywide median income across neighborhoods, denoted by $income_t^{city}$. For each neighborhood i, we then estimated a stable neighborhood-specific share,

$$s_i = \text{median}_t \left(\frac{y_{it}}{y_t^{city}} \right), \tag{9}$$

using months with valid observations. Residual missing values were then set equal to

$$\widetilde{y}_{it} = s_i \, y_t^{city}. \tag{10}$$

Overall, this procedure produces a stable and continuous measure of neighborhood income that preserves meaningful temporal variation while limiting the influence of sampling noise. This is particularly important for our analysis, which relies on cross-neighborhood differences in purchasing power to identify price-income relationships.

Online Appendix C. Product List and 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

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

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

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

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

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

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

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