Long-Run Retail Price Dispersion: Dynamics, Market Structure, and Chain Pricing*

Fernando Borraz† and Leandro Zipitría‡

Abstract

Using UPC-level supermarket prices for Uruguay spanning nearly sixteen years, this paper documents persistent long-run divergence in retail price dispersion within a single country. Contrary to the convergence implied by the Law of One Price, dispersion increases steadily over time. We show that this divergence is largely invisible in static analyses: once the relationship between price dispersion and market characteristics is allowed to evolve over time, the implied increase in dispersion more than doubles relative to baseline estimates. Retail price dispersion exhibits sharply different behavior within and across retail chains. Prices within chains remain tightly clustered and weakly responsive to local conditions, consistent with uniform or zone pricing. In contrast, economically meaningful divergence arises almost entirely across chains and is strongly associated with market structure, product differentiation, and competitive conditions. These findings highlight the central role of retail organization in shaping the long-run evolution of price dispersion and show that static approaches substantially understate persistent divergence in retail prices.

JEL Codes: D40, L11, L81, E31.

Keywords: Retail Price Dispersion, Law of One Price, Market Structure, Chain Pricing, Product Differentiation.

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†Banco Central del Uruguay and Departamento de Economía, Facultad de Ciencias Sociales, Universidad de la República. fernando.borraz@cienciassociales.edu.uy

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

1 Introduction

Understanding how prices differ across locations and sellers is central to both macroeconomics and industrial organization. A large literature documents long-run convergence toward the Law of One Price within and across countries, often interpreted as evidence that declining trade costs and market integration arbitrage away price differences. Within countries, this pattern has been documented for the United States (Parsley and Wei, 1996; O'Connell and Wei, 2002; Yazgan and Yilmazkuday, 2011), Canada (Ceglowski, 2003), China (Fan and Wei, 2006), and Mexico (Elberg, 2016). Across countries, convergence has been linked to reductions in trade barriers and currency frictions (Parsley and Wei, 2001; Crucini and Shintani, 2008; Cavallo, Neiman, and Rigobon, 2014; Broda and Weinstein, 2008), although mixed or slow convergence has been found in specific markets such as automobiles (Gil-Pareja, 2003; Goldberg and Verboven, 2005; Dvir and Strasser, 2018).

This paper shows that retail price dispersion exhibits markedly different behavior when studied using microdata over a long time horizon. Using UPC-level supermarket prices in Uruguay spanning nearly sixteen years, we document a systematic increase in retail price dispersion over time. Measured as the cross-store standard deviation of CPI-adjusted log prices within local markets, dispersion rises by 3.1–3.3 percentage points over the sample period. Allowing the relationship between price dispersion and market characteristics to vary over time reveals substantially stronger divergence. Once these time-varying relationships are taken into account, the implied increase in dispersion more than doubles, reaching approximately six percentage points. Rather than converging, retail prices in Uruguay display persistent long-run divergence.

Why Uruguay? Uruguay provides a particularly clean laboratory to study long-run retail price dispersion. It is a small country with no internal trade barriers, a single currency, and a uniform national monetary and regulatory framework. Our data cover all major supermarket chains and stores operating nationwide, and chain penetration in food retail is high, making chain-level pricing strategies empirically relevant. These features allow us to abstract from border frictions, exchange-rate movements, and regulatory heterogeneity, and to focus instead on how market structure and retail organization shape the evolution of price dispersion within a single country.

Our analysis adopts an explicitly dynamic perspective. We distinguish between cross-sectional differences in price dispersion across markets at a point in time and the evolution of those differences over time. Specifically, we examine whether market characteristics associated with higher cross-sectional dispersion are also associated with persistent divergence over time. Throughout the paper, these relationships are interpreted as reduced-form correlations rather than causal effects. Pricing strategies, product assortments, and market structure are jointly determined in retail markets, and their co-evolution over time is a central feature of the data.

We find that macroeconomic variables exhibit unstable and often transitory correlations with price dispersion. In contrast, microeconomic features—particularly store competition and persistent differences in product assortments within categories—are robustly associated with both higher cross-sectional dispersion and divergence over time. These time-varying patterns are largely invisible in purely cross-sectional analyses.

Related literature. An extensive literature studies convergence toward the Law of One Price within and across countries. Early work documents convergence within countries such as the United States (Parsley and Wei, 1996; O'Connell and Wei, 2002), Canada (Ceglowski, 2003), and China (Fan and Wei, 2006), while later contributions highlight persistence and heterogeneity using micro data (Crucini and Shintani, 2008). Cross-country studies link convergence to reductions in trade costs, currency unions, and product integration (Broda and Weinstein, 2008; Cavallo, Neiman, and Rigobon, 2014), although slow or incomplete convergence has been documented in specific markets (Goldberg and Verboven, 2005). Our contribution differs in focus: we document long-run divergence in retail prices within a country, where border frictions, tariffs, and exchange-rate movements are absent. Related evidence of divergence has previously been documented across European countries in the automobile market (Dvir and Strasser, 2018).

A related strand of the literature emphasizes the role of microeconomic heterogeneity in shaping persistent relative price movements. Crucini and Telmer (2020) show that much of real exchange rate variation arises from micro-level price dispersion rather than aggregate shocks. While their analysis focuses on international relative prices, their central insight—that persistent price movements reflect underlying microeconomic heterogeneity—carries over to our setting. Our results provide within-country retail evidence consistent with this view: macroeconomic variables are associated with only transitory fluctuations in price dispersion, whereas microeconomic characteristics of retail markets are systematically linked to long-run divergence.

A second strand uses micro-level price data to characterize retail price dispersion and its cross-sectional components. Seminal contributions document persistent dispersion across stores and products (Lach, 2002; Nakamura, 2008), while later work highlights the role of store heterogeneity, promotions, and pricing strategies (Nakamura, Nakamura, and Nakamura, 2011; Kaplan and Menzio, 2015; Hitsch, Hortaçsu, and Lin, 2021). These papers provide detailed decompositions of dispersion at a point in time or over limited time horizons. Our approach differs from the variance-decomposition frameworks used in these studies. Rather than allocating the level of dispersion across sources, we examine whether the relationship between price dispersion and observable market characteristics changes systematically over time, emphasizing dynamic associations rather than static variance shares, which is central to understanding long-run divergence.

Retail price dispersion has long been studied as a distinct phenomenon, reflecting the fact that retail markets differ fundamentally from frictionless or arbitrage-based settings typically emphasized in the Law-of-One-Price literature. Classic evidence documents substantial and persistent dispersion across stores and products even within narrowly defined local markets (Lach, 2002; Nakamura, 2008). Subsequent work highlights the role of store heterogeneity, product differentiation, consumer search, promotions, and pricing strategies in shaping retail prices (Nakamura, Nakamura, and Nakamura, 2011; Kaplan and Menzio, 2015; Hitsch, Hortaçsu, and Lin, 2021).

Importantly, a growing literature shows that retail prices are often set at the chain level—through uniform or zone pricing policies—(Adams and Williams, 2019; DellaVigna and Gentzkow, 2019), while in other contexts they respond systematically to local demand and cost conditions (Butters, Sacks, and Seo, 2022; Eizenberg, Lach, and Oren-Yiftach, 2021; Handbury, 2021; Handbury and Weinstein, 2014; Stroebel and Vavra, 2019). As a result, competition, product differentiation, and chain-level pricing strategies can generate price dispersion patterns that persist—and may even increase—over time, despite the absence of border frictions or exchange-rate movements.

Several studies analyze retail pricing in Uruguay using similar data. Borraz and Zipitría (2012) document pricing behavior in supermarkets, while Borraz and Zipitría (2022) highlight the role of product variety as a source of Law-of-One-Price deviations. More recently, Klaczko (2025) studies retail price dispersion in Uruguay using a variance-decomposition approach. Relative to this literature, our contribution is not the identification of new determinants but the documentation of long-run divergence and the role of time-varying associations in shaping dispersion dynamics.

Our paper makes three main contributions to the literature. First, it documents long-run retail price divergence within a small high-income country, contrasting with the convergence results emphasized in the Law-of-One-Price literature. Second, it shows that static approaches understate long-run dispersion by masking changes over time in the relationship between price dispersion and market characteristics. Third, it links dispersion dynamics to retail market organization by showing that long-run divergence arises primarily across retail chains rather than within them.

Because pricing strategies, product assortments, and local market structure jointly evolve in retail markets, we adopt a descriptive empirical approach. Our objective is to document how these endogenous features co-evolve with retail price dispersion over time, focusing on time-varying relationships rather than causal effects. The following sections examine whether the relationship between dispersion and observable market characteristics changes systematically over time.

The remainder of the paper is organized as follows. Section 2 presents the data.

Section 3 documents dispersion trends. Section 4 presents the empirical framework linking dispersion to market characteristics. Section 5 reports results on cross-sectional correlates and dynamic associations. Section 6 analyzes within- and between-chain dispersion. Section 7 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 the Ministry of Economy and Finance in Uruguay.[1] Retailers are required to report posted prices under a sworn statement, and misreporting is subject to penalties, ensuring that reported prices closely reflect prices posted in stores.

Supermarket sales in Uruguay are heavily concentrated in food and household consumption goods. In 2017, between 80 and 85 percent of total supermarket sales corresponded to grocery products—including food, personal care, and cleaning items—while the remaining 15 to 20 percent consisted of non-food products such as textiles, appliances, toys, and household goods. Supermarket chains account for approximately 70 percent of retail total 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, 2022, 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. Items are homogenized to ensure comparability, and each store must report the same specific variety throughout the sample period. For instance, all stores report Coca-

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

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 2011, the product list was updated, revising brand coverage in several categories and incorporating 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, which we treat as distinct markets in the analysis (e.g., sunflower oil and corn oil; or wheat flour 000 and wheat flour 0000, which differ in their baking uses). For a small number of categories, such as meat and bread, products are not identified at the UPC or brand level, and those categories were discarded. The complete list of products is reported in Appendix B.

The dataset includes detailed information on store characteristics, including exact geographic location (Universal Transverse Mercator coordinates), chain affiliation, and number of cashiers. The panel is unbalanced and covers up to 539 stores across Uruguay's nineteen political states and 54 cities. Montevideo, the capital and largest city, accounts for nearly 40% of the population and 54% of stores in the sample. In the empirical analysis, we define each city as a market, except for Montevideo, where neighborhoods constitute separate markets.

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 155 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 follows 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). Prices are deflated using the CPI to remove inflation-driven variation in dispersion.

Our final dataset consists of 4,940,552 monthly price observations. Table 1 reports descriptive statistics and summarizes the variables used in the empirical analysis.

Table 1: Summary Statistics.

	Stores			ECH	
	Mean	St. D		Mean	St. D
CPI Adjusted Log Price	3.272	0.545	Unemployment Rate	0.076	0.034
Std. dev. log price across stores ($SD^m_{it}/100$)	0.056	0.064	Log Population	10.457	1.579
Category Entropy	0.272	0.334	Log Av. CPI Adjusted Income$^{\blacktriangle}$	9.504	0.403
St. D. of Share of Product in Stores	0.048	0.051	St. D. of Adjusted Income	9.154	0.467
Number of Competing Stores*	2.747	3.736			
Sample Period	04/2007	12/2022		04/2007	06/2022
Number of Observations	4,940,552			-	
Number of Stores	539			-	
Number of Chains	23			-	
Number of Markets (location)	118			70	
Number of Products	125			-	
Number of Categories	42			-	

Notes: Except for CPI adjusted log price, mean and standard deviation are computed at the product–market–month level. SD^m_{it} is reported in log points in the table; in regressions we express dispersion in percentage points, i.e., $SD^m_{it} = 100 \times sd_j(\log p^m_{ijt})$. CPI base year is 2022 and prices are deflated accordingly. *Number of stores in the same market and month. $^{\blacktriangle}$Income is in December 2010 pesos.

3 Price Dispersion over Time

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, month t, and market m, we compute SD^m_{it}, the standard deviation across stores of the log CPI-adjusted price (multiplied by 100), and $\tilde{p}^m_{it}$, the corresponding cross-store average log CPI-adjusted price. This measure captures cross-sectional price dispersion for a given product across sellers in a local market at a given point in time.

To study how dispersion evolves, we estimate:

$$SD^m_{it} = \alpha + \alpha_i + \alpha_{mo} + \alpha^m + \beta\tilde{p}^m_{it} + \gamma t + \varepsilon^m_{it}, \tag{1}$$

where α_i, α_{mo}, and α^m denote product, calendar-month, and market fixed effects, respectively. We estimate Equation (1) by weighted least squares, using the number of stores used to compute SD^m_{it} as weights, and report standard errors clustered at the product–time level.

Table 2 reports the baseline results. Across all specifications, the estimated coefficient on the time trend is positive and statistically significant, indicating that retail price dispersion increases over time rather than converging. Adding product, market, or month fixed effects does not materially affect the estimated time coefficient. The estimated linear coefficient implies that over the 189-month sample period, price dispersion has increased by approximately 3.3 percentage points.[2] Figure 1 plots the fitted trends. As in Dvir and Strasser (2018), we allow for non-linear trends by including a quadratic term. Dispersion increases over time under both linear and quadratic specifications.

To assess whether price dispersion dynamics are stable over time, we split the sample at the median month (June 2015) and re-estimate Equation (1) separately for the two subsamples. This split is purely descriptive and does not aim to identify structural breaks or explain changes across periods. Instead, it serves to evaluate whether the time trend in price dispersion is stable over the sample or varies across subperiods. If the estimated trend is similar across subsamples, average cross-sectional relationships between price dispersion and market characteristics can be interpreted as time-invariant. Conversely, if the trend differs across periods, it is natural to examine whether the cross-sectional correlations themselves evolve, motivating the inclusion of the interaction of the time trend and market characteristics in the subsequent analysis. Table 3 shows that dispersion increases in both periods, but the increase is substantially larger in the second half of the sample.

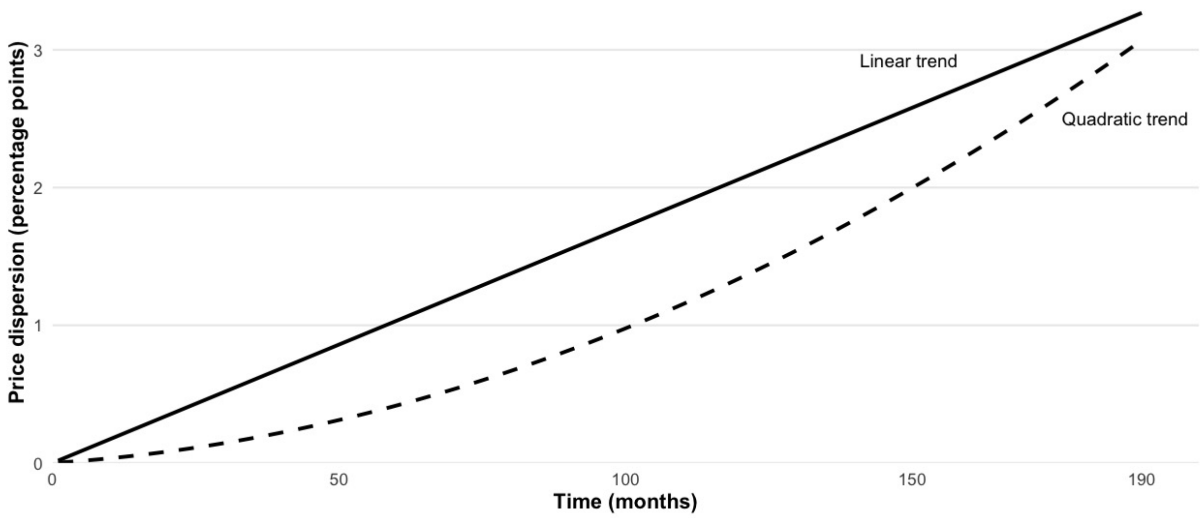
[2] Using the estimated coefficient on the linear time trend in Column (4) of Table 2, 0.0172, we obtain $3.3 = 0.0172 \times 189$. Since the dependent variable is measured in percentage points, this corresponds to an increase of 3.3 percentage points in price dispersion.

Table 2: Baseline Trend Estimation

Dependent Variable:	SD (in %)				
Model:	(1)	(2)	(3)	(4)	(5)
Constant	11.14***				
	(0.1517)				
Av. Price	-2.121***	-7.503***	-2.024***	-6.796***	-6.785***
	(0.0461)	(0.2006)	(0.0458)	(0.2005)	(0.2007)
Time	0.0179***	0.0160***	0.0192***	0.0172***	0.0027*
	(0.0005)	(0.0004)	(0.0005)	(0.0004)	(0.0014)
Time^2					7.08×10^{-5}***
					(7.54×10^{-6})
Product FE		Yes		Yes	Yes
Month FE		Yes	Yes	Yes	Yes
Market FE			Yes	Yes	Yes
Observations	1,008,944	1,008,944	1,008,944	1,008,944	1,008,944
R^2	0.056	0.166	0.121	0.224	0.225

Clustered (Product–Time) standard errors in parentheses.
Significance: *** 1%, ** 5%, * 10%.

Figure 1: Price Dispersion over Time



Notes: Estimates are computed using the linear trend coefficient from Column (2) and the quadratic trend coefficient from Column (3) of Table 2.

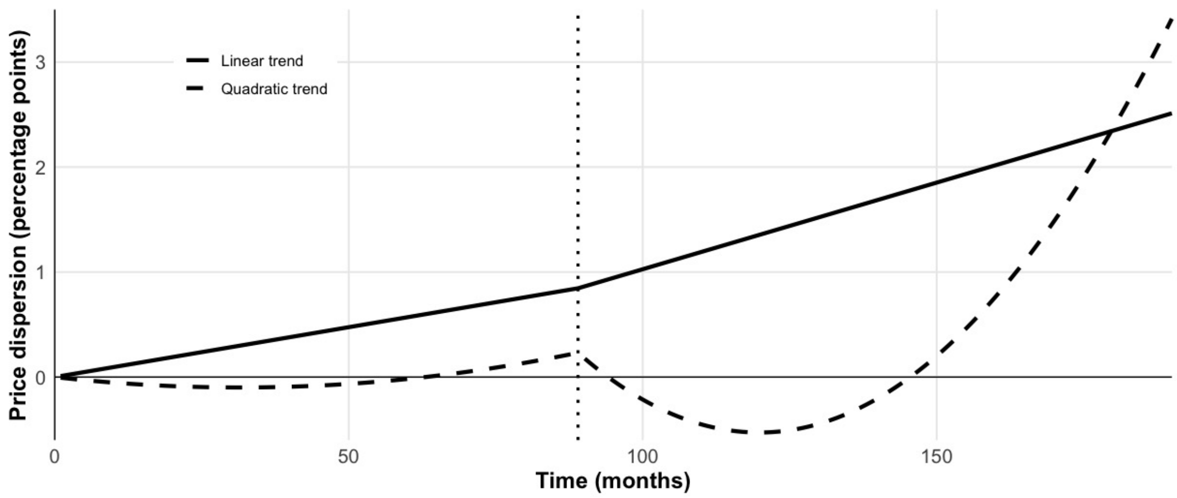
Finally, because the dataset is an unbalanced panel, increasing dispersion could mechanically reflect the entry and exit of stores. To address this concern, we restrict the sample to stores active in 2007 and re-estimate the model. Table 4 shows that the upward trend

Table 3: Trend Estimation: Before and After June 2015

Dependent Variable:	SD (in %)			
Model:	Before June 2015		After June 2015	
Av. Price	-3.636***	-3.575***	-10.24***	-11.01***
	(0.2074)	(0.2088)	(0.3621)	(0.3795)
Time	0.0095***	-0.0063**	0.0165***	-0.0493***
	(0.0006)	(0.0026)	(0.0014)	(0.0056)
Time^2		0.0001***		0.0008***
		(2.23×10^{-5})		(6.56×10^{-5})
Product FE	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	537,777	537,777	471,167	471,167
R^2	0.22932	0.22983	0.26236	0.26495

Clustered (Product–Time) standard errors in parentheses.

Figure 2: Price Dispersion over Time: Split Sample



Notes: Estimates are computed using the linear trend coefficient and the quadratic trend coefficient of Table 3.

remains and is not driven by store turnover.

Overall, dispersion increases persistently over time, with a particularly pronounced rise after 2015.

Table 4: Trend Estimation: Stores Active in 2007

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

Clustered (Product–Time) standard errors in parentheses.

4 Empirical Framework: Price Dispersion and Market Structure

This section defines the empirical framework linking price dispersion to market characteristics. Our objective is not to identify causal effects, but to assess whether the same characteristics associated with cross-sectional differences in dispersion are also associated with dynamic divergence or convergence over time. Throughout, coefficients should be interpreted as reduced-form correlations: retail prices, market structure, and product assortments are jointly determined, and endogeneity is a feature of retail data.

4.1 Empirical specification

Our unit of observation is a product–market–time price. Let SD_{it}^m denote price dispersion in market m at time t for product i, measured as the cross-store standard deviation of CPI-adjusted log prices expressed in percentage points. Let X_{mt} denote a vector of observable market characteristics measured at the market–time level.[3]

[3]Some micro variables vary at the market–time–category level; we assign them to each product observation belonging to that category.

We begin with a baseline specification relating dispersion to cross-sectional market characteristics:

$$SD_{it}^{m} = \alpha + \beta X_{mt} + \alpha_i + \alpha_{mo} + \alpha^m + \varepsilon_{it}^{m}, \tag{2}$$

where α_i, α_{mo}, and α^m denote product, calendar-month, and market fixed effects, respectively. The coefficients β capture cross-sectional differences in dispersion associated with market characteristics.

To study time-varying relationships, we allow these relationships to vary over time by interacting X_{mt} with a linear time trend:

$$SD_{it}^{m} = \alpha + \beta X_{mt} + \gamma(X_{mt} \times t) + \alpha_i + \alpha_{mo} + \alpha^m + \varepsilon_{it}^{m}. \tag{3}$$

The interaction coefficients γ capture whether the association between dispersion and a given market characteristic strengthens or weakens over time.

This interaction between observable market characteristics and a time trend is a central feature of our empirical approach. It is motivated by the premise that the same features explaining cross-sectional differences in price dispersion at a given point in time may also shape how that dispersion evolves as markets mature. This is relevant because of the sixteen years of our database.

From an economic perspective, retail markets are characterized by gradual adjustments in pricing strategies, product assortments, and consumer search behavior. Consequently, variables such as local competition or product differentiation may generate effects that accumulate over time, leading to persistent divergence or convergence in prices. A static specification would restrict these relationships to be constant over the sample period, thereby overlooking time-varying effects.

This econometric approach relaxes the restrictive assumption that the association between price dispersion and its market correlates—such as the number of competitors or the degree of product differentiation—is time-invariant. In a standard static model, the implicit constraint is that the marginal effect of any market characteristic is fixed at a single value throughout the study. This assumes, for instance, that an increase in competition reduces price dispersion by the same magnitude in the first month as it does five years later. However, such an assumption is often unrealistic in evolving markets, where price sensitivity to competition may intensify as consumers become more informed. By allowing the coefficients to vary over time, we accommodate temporal heterogeneity in the parameters. These interaction terms capture whether the marginal relationship between dispersion and a specific characteristic systematically strengthens or weakens over time, without imposing discrete breaks or relying on specific aggregate shocks.

Accordingly, the coefficients on the interaction terms indicate whether cross-sectional market differences associated with a given characteristic tend to widen or narrow over time. This distinction between cross-sectional differences and their dynamics is central to our contribution to the study of price dispersion.

4.2 Market characteristics: micro and macro

Based on the literature, we analyze seven market characteristics grouped into three microeconomic and four macroeconomic variables.

Microeconomic characteristics. Micro characteristics are typically endogenous to price dispersion. Retailers jointly choose prices, assortments, and entry/exit strategies in response to local market conditions. Our objective is to document whether these characteristics co-move with dispersion cross-sectionally and dynamically.

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 between products rather than competition between stores, consistent with defining markets at the product-category level (e.g., Nakamura, 2008; Kaplan and Menzio, 2015; Hitsch, Hortaçsu, and Lin, 2021) and 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 shows mean $E_t^{m,c} = 0.272$ and standard deviation 0.334. We expect this coefficient to be positive; i.e., larger differences in the number of products a store offers 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 0.048 and standard deviation 0.051. 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 competition across markets. Following Berardi, Sevestre, and Thébault (2017), we define:

$$N_t^m = \sum_{j \in J_t^m} \mathbf{1} - 1,$$

where J_t^m is the set of stores operating in market m at time t. The mean number of competitors is 2.747 (sd 3.736). More competition between stores has an ambiguous effect on price dispersion. On the one hand, greater competition puts pressure on prices to converge, as consumers can easily arbitrage across more stores. On the other hand, as the number of stores increases, search costs also increase (Varian, 1980; Lach, 2002). Kaplan, Menzio, Rudanko, and Trachter (2019) call this effect relative price dispersion, which is the difference between stores in the price of the same good relative to the prices of other goods at that store. If the first effect dominates, the coefficient should be negative—more stores imply less price dispersion—, if the second effect dominates, the coefficient should be positive.

Macroeconomic characteristics. We also consider four macro variables commonly used in the literature. We include the unemployment rate (UR_t^m, Daruich and Kozlowski (2023)), market size measured by log population (Pop_t^m, Handbury and Weinstein (2014), Berardi, Sevestre, and Thébault (2017), Daruich and Kozlowski (2023)), log income (Inc_t^m, Handbury (2021), Berardi, Sevestre, and Thébault (2017)), and income dispersion ($SDInc_t^m$, Frankel and Gould (2001)). These variables are computed over three-month windows at the neighborhood level in Montevideo and the department level elsewhere.

Macroeconomic variables operate through microeconomic variables. For example, Handbury (2021) showed that in richer markets, stores offer a larger product assortment. According to the literature, we expect a larger price dispersion—i.e., a positive sign—for markets with higher income (Handbury, 2021), larger population (Handbury and Weinstein, 2014), larger unemployment (Daruich and Kozlowski, 2023), and more unequal income distribution (Frankel and Gould, 2001). Nevertheless, after controlling for differences in store assortment, the effects of the macroeconomic variables remain less clear.

4.3 Implementation

We incorporate these seven variables into the dispersion equation:

$$\begin{aligned} SD_{it}^m &= \alpha + \alpha_i + \alpha_{mo} + \alpha^m + \beta \tilde{p}_{it}^m + \gamma t \\ &\quad + \underbrace{\eta_1 E_t^{m,c} + \eta_2 N_t^m + \eta_3 SDP_t^m}_{\text{micro}} + \underbrace{\theta_1 UR_t^m + \theta_2 Pop_t^m + \theta_3 Inc_t^m + \theta_4 SDInc_t^m}_{\text{macro}} + \varepsilon_{it}^m. \end{aligned} \tag{4}$$

In the next section, we extend this specification by interacting the market characteristics with time to identify dynamic associations.

5 Empirical Results: Drivers of Price Dispersion

This section reports empirical results on the drivers of retail price dispersion. We proceed in two steps. First, we study cross-sectional correlations between price dispersion and market characteristics. Second, we study how the relationship between price dispersion and market characteristics evolves over time by interacting these variables with a time trend.

5.1 Cross-sectional correlates

Table 5 reports estimates of Equation (4). All specifications include product, market, and month fixed effects, are estimated by weighted least squares using the number of stores as weights, and report standard errors clustered at the product–time level. Results are reported for the full sample and separately for the periods before and after June 2015.

Several results stand out. First, microeconomic variables are robust cross-sectional correlates of price dispersion. Category entropy and store competition are positively and significantly associated with dispersion in all periods. Markets with more differentiated assortments within categories and with more competing stores exhibit systematically higher price dispersion.

Second, the role of macroeconomic variables is less stable over time. Unemployment is positively associated with price dispersion before 2015 but becomes statistically insignificant thereafter. Market size (population) is negatively associated with dispersion only in the post-2015 period. These patterns suggest that macroeconomic conditions correlate with dispersion in a time-varying manner rather than exerting a stable relationship across periods.

Third, the coefficient on the time trend is statistically significant in the full sample

Table 5: Cross-sectional correlates of price dispersion

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

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

and in the pre-2015 subsample, but not in the post-2015 period. This should not be interpreted as a slowdown in dispersion dynamics. Earlier results show that aggregate dispersion rose more rapidly after 2015. Instead, the absence of a significant residual time trend in the second period indicates that observable market characteristics account for most of the dispersion's evolution during this phase. In other words, post-2015 dispersion dynamics operate primarily through changes in market structure and related covariates, leaving little of the common time component unexplained.

Finally, while all significant coefficients are positive in the full sample and in the period before the median, several coefficients reverse sign after 2015, including those for product variety dispersion, population, and income. These sign reversals reinforce the view that the correlates of price dispersion are not stable over time and motivate our subsequent focus on dynamic interactions between market characteristics and time.

To gauge magnitudes, we use the full-sample estimates together with the standard deviations reported in Table 1. A one-standard-deviation increase in category entropy (0.334) is associated with an increase in dispersion of $0.4914 \times 0.334 \approx 0.164$ percentage points, or nearly 30% of the standard deviation of price dispersion. A one-standard-deviation increase in competition (3.736) is associated with an increase in dispersion of $0.1598 \times 3.736 \approx 0.597$ percentage points, which corresponds to approximately 110% of the standard deviation of price dispersion. By comparison, a one-standard-deviation increase in the unemployment rate (0.034) is associated with an increase of $2.449 \times 0.034 \approx 0.083$ percentage points, or about 15% of the standard deviation. These magnitudes reinforce the view that microstructure—particularly competition and within-category differentiation—is the most important set of cross-sectional correlates.

5.2 Time interactions

Cross-sectional correlations do not reveal whether the same market characteristics are associated with persistent divergence over time. To study time-varying relationships, we augment Equation (4) by interacting each market characteristic with the time trend:

$$
\begin{aligned}
SD_{it}^{m} = \alpha + \alpha_i + \alpha_{mo} + \alpha^m + \beta \tilde{p}_{it}^{m} + \gamma t \\
&+ \eta_1 E_t^{m,c} + \eta_2 N_t^m + \eta_3 SDP_t^m + \theta_1 UR_t^m + \theta_2 Pop_t^m + \theta_3 Inc_t^m + \theta_4 SDInc_t^m \\
&+ \delta_1 (E_t^{m,c} \times t) + \delta_2 (N_t^m \times t) + \delta_3 (SDP_t^m \times t) \\
&+ \kappa_1 (UR_t^m \times t) + \kappa_2 (Pop_t^m \times t) + \kappa_3 (Inc_t^m \times t) + \kappa_4 (SDInc_t^m \times t) \\
&+ \varepsilon_{it}^m .
\end{aligned}
\tag{5}
$$

Table 6 reports the coefficients on t and the interaction terms (level coefficients and fixed effects are included but omitted for brevity) for the full sample database.

Table 6: Dynamic associations: time interactions

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

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

Two conclusions emerge from Table 6. First, once time interactions are included, the estimated coefficient on the time trend increases substantially relative to the baseline specification (Table 2, column (4)), implying a larger cumulative rise in dispersion over the period. This indicates that the unconditional trend masks offsetting forces embedded in market characteristics whose relationships with dispersion change over time.

Even when the coefficient on the time trend remains statistically significant, its interpretation changes once market characteristics and their interactions with time are introduced. In this specification, the time coefficient captures the residual evolution of price dispersion not explained by observed structural features. This indicates that long-run divergence operates primarily through changes in market structure rather than through an unexplained common time component.

Second, microeconomic variables differ sharply in their time interactions. Category entropy and competition exhibit positive, statistically significant interactions with time, suggesting that markets with more differentiated assortments and stronger competition experience persistent divergence in price dispersion. By contrast, several macroeconomic interactions are negative, consistent with the view that macroeconomic conditions are associated with transitory or offsetting movements in dispersion rather than persistent divergence.

In terms of magnitude, the time interaction for category entropy is economically meaningful. It implies that within-category assortment differentiation is not only a cross-sectional correlate of price dispersion but also a key variable associated with long-run divergence. Taken together, these results indicate that persistent divergence in retail price dispersion is primarily linked to microeconomic market structure rather than to aggregate macroeconomic conditions.

The results in this section show that persistent divergence in retail price dispersion is closely linked to microeconomic market characteristics and that these relationships vary over time. However, these aggregate patterns do not reveal whether divergence arises from price dispersion within retailers or from differences across retailers. In particular, the strong role of competition, product differentiation, and time-varying associations raises the question of whether dispersion dynamics operate primarily within or across retail chains.

To address this question, the following section exploits the chain structure of the data to decompose price dispersion into within-chain and between-chain components and to examine how their levels and dynamics differ. This distinction is central to understanding the sources of long-run divergence, since pricing decisions are often made at the chain level rather than by individual stores.

6 Chains

Retail chains play a central role in price-setting behavior. A large body of literature shows that stores within the same chain tend to follow uniform or zone pricing policies and display substantially less price dispersion than independent stores or stores belonging to different chains (Nakamura, Nakamura, and Nakamura, 2011; DellaVigna and Gentzkow, 2019). This section exploits the chain structure of the data to distinguish between within-chain and between-chain price dispersion and to examine how their levels, correlations, and dynamics differ over time.

6.1 Data construction: within- and between-chain databases

Our dataset contains both independent stores and stores belonging to retail chains. To isolate within-chain and between-chain sources of dispersion, we construct two complementary databases.

First, we restrict the sample to chain stores and construct a within-chain database. Price dispersion is recalculated at the product–market–chain–time level, denoted $SD_{it}^{m,s}$. All microeconomic variables are recomputed at the market–chain–time level (or at the category–chain–time level when relevant). We further decompose local competition into two components: competition from stores outside the chain,

$$NComp_t^m = \sum_{j \in J_t^m, j \notin S} \mathbf{1} - 1,$$

and competition from stores within the same chain,

$$NCh_t^m = \sum_{j \in J_t^m, j \in S} \mathbf{1} - 1.$$

Second, we construct a between-chain database by collapsing the data to the chain–market–time level. For each product i, market m, and month t, we define p_{istm} as the median log CPI-adjusted price across stores belonging to chain s. Between-chain price dispersion is then computed as

$$SD_{it}^{m,\text{between}} = 100 \times sd_s(\log p_{istm}) \, ,$$

so that dispersion reflects differences in pricing across chains operating in the same market, rather than differences across stores within a chain. Analogously, within-chain dispersion is computed as the cross-store standard deviation of log prices within a given chain, market, and time.

6.2 Dispersion trends: within vs. between chains

We estimate Equation (1) separately for the within- and between-chain databases, allowing for linear and quadratic trends. In both samples, we include product and month fixed effects. In the within-chain sample, we additionally include market–chain fixed effects, while in the between-chain sample, we include market fixed effects. Observations are weighted by the number of stores associated with each chain–market cell, and standard errors are clustered at the product–time level.

Table 7 documents stark differences in both the level and the dynamics of price dispersion within and between retail chains. Dispersion within chains is tightly clustered, whereas dispersion between chains is substantially larger. Consistent with this pattern, the mean absolute price deviation within chains is 0.01, compared to a median deviation of 0.066 between chains, and the standard deviation of dispersion is 0.03 within chains versus 0.069 between chains. These magnitudes indicate that economically meaningful price dispersion primarily reflects differences across chains rather than heterogeneity within chains.

The dynamics of price dispersion also differ sharply across these two dimensions.

Table 7: Trend estimation: within and between chains

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

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

Within chains, dispersion exhibits little systematic long-run trend, suggesting stable relative pricing across stores belonging to the same chain. In contrast, dispersion between chains shows a strong, increasing time trend, with both linear and quadratic terms indicating accelerating divergence. This pattern implies that long-run retail price divergence arises predominantly from widening price differences across chains rather than from increasing dispersion within chains.

To gauge the economic magnitude of these trends, consider a simple counterfactual. After 100 periods, a one-standard-deviation change in price dispersion would raise dispersion within chains by only 0.000015—computed as $0.0005 \times 100 \times 0.03 \times 0.01$. In contrast, the corresponding increase between chains is approximately 0.01—computed as $0.0228 \times 100 \times 0.069 \times 0.066$—equivalent to about 0.1 percent of observed price differences. This stark contrast underscores that economically meaningful long-run divergence is overwhelmingly a between-chain phenomenon.

Consistent with this interpretation, the linear and quadratic time terms are positive and statistically significant for dispersion between chains. At the same time, their magnitudes are small, or their signs are ambiguous within chains. Appendix A (Table 10) further shows that prices within chains display convergence up to the median period, whereas dispersion between chains increases sharply. After the median date, within-chain prices exhibit weak and imprecise divergence, while between-chain dispersion continues to rise.

6.3 Cross-sectional correlates: within vs. between chains

We next estimate Equation (4) separately for the within- and between-chain databases. Coefficients in this section should be interpreted as reduced-form correlations rather than in terms of magnitudes, as both the level and the dynamics of dispersion differ substantially across these two dimensions.

Once observable market characteristics are included, the residual time trend for dispersion within chains becomes statistically insignificant. In contrast, the residual time trend for dispersion between chains remains significant and economically meaningful. This distinction becomes sharper after the median date (June 2015). In the post-2015 period, the residual time trend is no longer statistically significant after controlling for market-level covariates, indicating that the earlier-observed acceleration in aggregate dispersion is mainly explained by changes in observable market characteristics rather than by an unexplained common trend.

Macroeconomic correlates display markedly different patterns within and between chains. Except for market size, dispersion within chains does not respond systematically to macroeconomic conditions. This result is consistent with evidence that retail chains tend to set uniform prices across stores and therefore react weakly to local market environments (DellaVigna and Gentzkow, 2019). The negative coefficient on population in the within-chain regressions likely reflects that chains operate more stores in larger markets, leading—conditional on other factors—to lower dispersion within chains. In contrast, market size is not significantly associated with dispersion between chains.

Table 8: Cross-sectional correlates: within and between chains

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

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

By comparison, dispersion between chains increases with local unemployment and income inequality within markets, suggesting that macroeconomic heterogeneity affects relative pricing across chains rather than within them. Differences in average income across markets, however, are associated with lower dispersion, indicating that pricing responds more strongly to inequality within markets than to differences across markets.

Microeconomic correlates also differ sharply across dimensions. Given that dispersion between chains is an order of magnitude larger than within chains, coefficients should be interpreted comparatively rather than in absolute terms. Within chains, dispersion responds most strongly to the presence of other stores belonging to the same chain. In contrast, dispersion between chains increases with the number of competing stores in the market. Differences in product variety are positively associated with dispersion in both samples; however, the response within chains is substantially stronger—approximately 1.5 times larger—than that between chains, indicating that assortment differences play a particularly important role in shaping within-chain dispersion.

Appendix A (Table 11) reports estimates separately for the periods before and after the median date. These results show that correlations within chains vary considerably over time, whereas microeconomic factors are more stable and consistently associated with greater dispersion across chains.

6.4 Time interactions: within vs. between chains

Finally, we estimate the time-interaction specification, analogous to Equation (5), separately for each database. Table 9 reports the estimated time trends and interaction coefficients.

These results further reinforce the central message of the paper: long-run price divergence is overwhelmingly a between-chain phenomenon. Within chains, price dispersion is very low, and although some interactions between time and microeconomic variables are statistically significant, their economic impact remains limited. These effects operate on a small baseline level of dispersion, implying modest cumulative contributions over time. Moreover, once market characteristics are controlled for, the time trend within chains becomes insignificant in the full sample. It reverses sign across subsamples—negative before June 2015 and positive thereafter—indicating the absence of a stable autonomous trend.

By contrast, between chains, the time interactions are large, stable, and economically meaningful. The time trend remains positive in the full sample, and interactions with key microeconomic variables—such as category entropy and competition—are consistently

Table 9: Dynamic associations: within and between chains

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

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

positive. This implies that markets with more differentiated assortments and stronger competitive pressure exhibit persistent, cumulative divergence across chains. Macroeconomic interactions further highlight this asymmetry: unemployment and income inequality display significant time interactions between chains, while remaining weak within chains.

Importantly, after June 2015, once market-level covariates (and their time interactions) are included, the residual time trend between chains becomes statistically insignificant.

This result should not be interpreted as a slowdown in divergence. Instead, it indicates that post-2015 between-chain divergence is largely captured by the evolution of observable market structure and composition rather than by an unexplained common time component.

Taken together, these results show that price dispersion does not evolve in a linear or additive fashion. Within-chain dispersion remains low and sensitive to changing correlations over time, whereas between-chain dispersion follows a persistent divergence path driven by microeconomic differentiation and competitive forces. Both the level and the dynamics of retail price dispersion are therefore shaped primarily by differences across chains rather than by heterogeneity within chains.

7 Conclusion

This paper documents persistent long-run divergence in retail price dispersion within a single country, challenging the convergence patterns emphasized in the Law-of-One-Price literature. Using detailed supermarket price data for Uruguay, we show that retail price dispersion increases systematically over time, even in the absence of border frictions, exchange-rate movements, or trade barriers.

A central finding is that this divergence is overwhelmingly a between-chain phenomenon. Prices within retail chains remain tightly clustered and display weak responsiveness to local market conditions, consistent with uniform or zone pricing. In contrast, dispersion across chains is substantially larger and increases persistently over time. Once market characteristics and their evolution are taken into account, little of the observed long-run divergence is left unexplained by structural features of retail markets.

These findings contribute to three strands of the literature. First, we provide evidence of long-run retail price divergence within a country, complementing studies that emphasize convergence in other contexts. Second, we show that static approaches understate long-run dispersion by masking the evolution of the relationship between prices and market characteristics over time. Third, we highlight the central role of retail organization, showing that chain-level pricing strategies are key to understanding both the level and the evolution of retail price dispersion.

Our analysis is descriptive and does not aim to identify causal effects. Pricing strategies, market structure, and product assortments are jointly determined and evolve endogenously. Understanding the mechanisms underlying these patterns—such as strategic pricing, consumer heterogeneity, and entry and expansion decisions—remains an important avenue for future research.

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A Additional Tables

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

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

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

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

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

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

B Product Characteristics (Not for Publication)

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

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

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

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

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

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

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

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

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

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

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

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