Retail Prices: New Evidence From Argentina*

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Abstract

We create a new database of retail prices in Argentina with over 10 million observations per day. Our main novel finding is that, different from Kaplan, Menzio, Rudanko, and Trachter (2016), chains, rather than stores, explain most of the price variation in our data. We show this in three ways: (a) Even though chains have on average 158 stores, there are on average less than 2.5 unique prices per product by chain; (b) Among products that change prices in one store, the probability that other stores of the same chain also change the price of the same product in the same day is 2.4 times the probability for other stores of any chain; and (c) A formal variance decomposition shows that only 28% of the price dispersion (for the same product, day, and city) is explained by stores setting different prices within a chain. This finding is relevant for retail-pricing theories since there are significantly fewer chains than stores, which matters for the degree of competition in the market. This paper also studies the heterogeneity in price changes and price dispersion across product categories.

JEL Classifications: L11, D40, E31 .

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1 Introduction

Most empirical analysis about micro-price statistics use scanner price data and focuses on developed and low-inflation countries. We complement this literature by creating a new database for daily prices of retail stores in Argentina in a high-inflation context. In this paper we use this database to study the role of chains in retail prices. Kaplan, Menzio, Rudanko, and Trachter (2016) documents that "a significant fraction of the cross-sectional variation in the price at which the same good is sold in the same period of time and in the same market is due to the fact that retailers [stores] that are, on average, equally expensive set persistently different prices for that particular good." Our main novel finding is that it is chains rather than stores that explain most of the price variation in our data. This finding is relevant for retail-pricing theories since there are significantly fewer chains than stores, which matters for the degree of competition in the market.

We scrape a large dataset about retail prices in Argentina. Since May 2016, every day stores have to report their offline prices (i.e., prices in the store) to the government. The data is processed and posted online in an official price-comparison website with the objective of providing information to consumers. One of this paper's contributions is the collection of high-frequency price data from a developing country in a high inflation regime (about 30% in 2016). We web-scrape about 10 million prices per day, allowing us to have a large panel on stores, products, and prices. For each store, we know its chain owner, the type of store, and its precise location. Stores within a chain are categorized by types, either due to store's sizes or brand names. For each product (UPC bar code), we know its name, category, and brand. For each day-store-product we observe both list and sale prices. One disadvantage is that we have posted prices, not transaction prices nor quantities sold. However, having daily posted prices for all products (not just the ones being sold or bought) can be useful to understand price setting strategies. In the main analysis of the paper we focus in the capital (Buenos Aires City, CABA) which is the biggest local market of Argentina.

Our main novel finding is that chains, rather than stores, explain most of the price variation. We present three pieces of evidence consistent with this fact. First, even though chains have on average 158 stores, we find that there are on average less than 2.5 unique prices per product by chain. Second, price changes are also consistent with this finding. Focusing on products that change prices in one store, we compute the probability that other stores change the price of the same product in the same day. This probability is 16.5% for stores of *any* chain, but it increases to almost 40% when we focus on stores of the *same* chain. If we focus only on stores of the same type within the chain, this share increases to almost 62%. Moreover, the intensive margin of price changes is also similar within chains: the dispersion of these price changes within a chain is less than one-fifth of the one observed in the whole economy. Third, we define the relative price of a product in a store and day as its price expressed as the percentage deviation from the average price in the relevant day. We decompose the variance of relative prices into three components: (i) Chain fixed effect, to capture that some chains may be on average more expensive; (ii) Chain-product fixed effect, to capture that equally expensive chains may set different relative prices across products; and (iii) Residual, to capture that different stores within each chain may set different prices for the same product. We find that 72% of the relative price dispersion can be explained by chain (one-fourth of 72%) and chain-product fixed effects (three-fourth). Hence, only 28% of the price variation can be explained by stores setting different prices within a chain.

A large fraction of the relative price dispersion is explained by the chain-product interaction. A possible reason could be that each chain sets relative prices independently across products. We find evidence that this is not the case by looking at the correlation of relative prices across chains. We compute the average relative price for each chain and product category (e.g., frozen food, personal care, or non-alcoholic beverages), and study how correlated relative prices are across categories. For example, the correlation between frozen food and grocery is -0.89 while the one between frozen food and non-alcoholic beverages is 0.74. The mean absolute correlation is 50%, which suggests that chains set prices in a systematic way. We find that categories with larger price dispersion are associated with higher absolute correlation.

We further study the heterogeneity across product categories and show that price changes (both extensive and intensive margins) and price dispersion vary across categories. Regarding the extensive margin of price changes, on average 2.17% of products increase prices daily but this share is between 1.6 and 2.4% depending on the category (similar differences are present for price decreases). Regarding the intensive margin, the standard deviation of absolute price changes is always smaller (up to one-third) within categories than in the whole sample. These statistics are important to understand the real effects of monetary policy in New Keynesian models, suggesting that real effects may differ across product categories. Relative price dispersion also varies across categories. Price dispersion is 6.7% in the whole sample, but it can be as low as 5.3% for alcoholic beverages, and as high as 7.8% for frozen food. Under the lens of search models, price dispersion is important to identify how captive consumers are, so our evidence may be interpreted as consumers of some products may be more captive than others. In addition, we find that categories with high price dispersion are associated with both higher share and larger absolute sizes of price changes.

The rest of the paper is organized as follows. Section 2 reviews the literature. Section 3 describes the web-scraping and the characteristics of the data. We present our findings about chains, price changes and price dispersion in Sections 4, 5, and 6. Section 7 studies heterogeneity across products' categories. Finally, Section 8 concludes. Additional results are gathered in Appendix A.

2 Related literature

This paper is related to the empirical literature on price-setting behavior in high-inflation countries. Alvarez, Beraja, Gonzalez-Rozada, and Neumayer (2016) also study micro-price statistics for Argentina, but in a different period (1988 to 1997) and with a smaller sample.[1] Different from previous research, we have larger cross-sectional variation in stores and products which allows us to control for observable characteristics and uncover novel empirical facts. For example, in Alvarez, Beraja, Gonzalez-Rozada, and Neumayer (2016) the average number of observations per month is about 81,000 whereas we have about 10 million observations per day. Similarly, they have information on 500 goods, whereas we have 2,794 products. This paper is also related to the empirical literature about gathering new data on retail prices in developing countries. Cavallo and Rigobon (2016) provides a summary of this new research agenda. Our contribution is that we obtain access to information about offline prices (i.e., in the store) instead of online prices as in previous research.

Regarding price adjustments, Midrigan (2011) uses data on a single chain in the U.S. and finds evidence of price change synchronization within stores. We confirm the finding in our data for Argentina. Moreover, we extend the analysis and also find synchronization on the extensive and intensive margins of price changes within chains.

Our empirical findings about price dispersion are related to the analysis on Nakamura, Nakamura, and Nakamura (2011) and Kaplan, Menzio, Rudanko, and Trachter (2016) for the U.S. Previous papers used scanner price data with the disadvantages of being at weekly frequency and with transaction prices which mix temporary sales with list prices. A distinct feature of

[1] See also Lach and Tsiddon (1992); Eden (2001); Baharad and Eden (2004) for Israel, Gagnon (2009) for Mexico, and Konieczny and Skrzypacz (2005) for Poland. All of these datasets are much smaller than ours (see data comparisons in Alvarez, Beraja, Gonzalez-Rozada, and Neumayer (2016)).

our data is that we observe daily list prices which allow us to get a more granular definition of goods. Our empirical strategy is similar to Kaplan, Menzio, Rudanko, and Trachter (2016) but we also control for chains effects. Interestingly, Nakamura, Nakamura, and Nakamura (2011) also finds evidence of a large chain component in price setting.

That micro-price statistics are heterogeneous across categories is well established in the data (e.g., Nakamura and Steinsson, 2008; Klenow and Malin, 2010). We show how these heterogeneity covaries with price changes, price dispersion, and price correlations (between categories). We are not aware of other papers that offer an empirical study the correlation of prices across products' categories.

3 Data

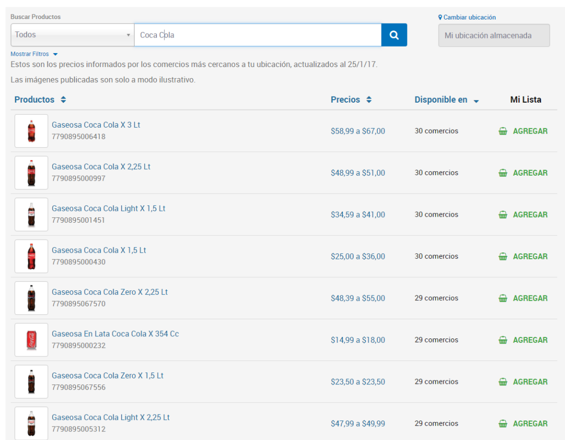
In February 2016, the Argentinean government passed a normative to build a national, publicly available report of prices (*Sistema Electronico de Publicidad de Precios Argentinos*). The objective of the policy was to reduce inflation, by providing information on prices. All large retailers of massively consumed goods have to report daily prices for each of their stores. The requirement was mandatory for a large set of products (typically associated with grocery stores), but retailers were allowed to include non-mandatory ones as well. Large fines (of up to 3 million U.S. dollars) are to be applied if stores do not report their prices correctly. From May 2016, the official website `www.preciosclaros.gob.ar` provides consumer-friendly access to this price information. On this website, after entering their location, consumers can search for stores and products and compare their current prices. This website only contains information about the prices in the stores, i.e., consumers cannot buy online from this website. In this paper we use data from May 2016 to February 2017.

Figure 1 shows an example in which this website is used to search for Coke (*Coca Cola*) soda. The second figure shows that after searching for *Coca Cola*, many varieties of the product are available. The range of prices in the (30) nearby stores are reported. After selecting one particular product (e.g., *Gaseosa Coca Cola X 2,25Lt*), we obtain the list of stores and their prices. Note that these prices include list and sale prices. This is explained in more detail below.

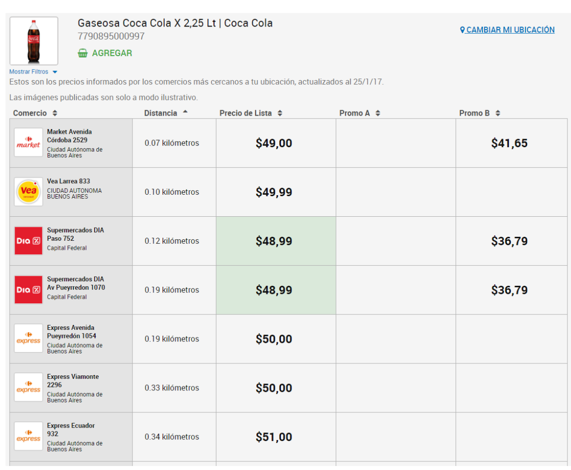
Figure 1: **Precios Claros Website**.

Step 1: Introduce location

Step 2: Search for product



Step 3: Select product



Source: Precios Claros. We show here an example in which the website is used to search for Coke (Coca Cola) soda. The last figure shows (a subset) the different stores and set of prices (including sales) available nearby.

In order to report the information, each store has to upload its prices daily to a server before 6AM.[2] Everyday, we run a customized software designed to scrape the daily information on stores, products, and prices posted online. We then put all the information together, creating a panel with the scraped information on stores, products, and prices to use in our analysis.

We are able to obtain information on each store and product. For each store, we scrape information on its name (not just an identification code), its chain owner, the type of store (e.g., small or large supermarkets), and its precise location (latitude and longitude). Chains may have different types of stores due to alternative sizes of stores (e.g., Express, Market, and Supermarket) or due to stores known under different names in the market. For example, the chain *Jumbo* acquired the chains *Vea* and *Disco*, so it also includes them as different types of stores. For each product (bar code), we know its name, category, and brand. Categories are composed of three levels, with the third level being the most disaggregated. For example, the first level categories include personal care and non-alcoholic drinks. The second level of the personal care category includes hair care and oral care. Finally, the third level of hair care includes categories like shampoos and conditioners.

The price posted in the website is the price available at each (offline) store. Given that some products have special sales, we sometimes have several prices for a good in a particular store and day. In such cases, we scrape all available prices. Some of these sales are only available to some type of consumers—typically a percentage discount for customers with a particular credit card or membership. However, some of these sales also refer to discounts available to all consumers—for example, two for the price of one. Each store must report the list price and can report up to one of each of these two types of sale prices.[3] Importantly, we are able to differentiate these two types of sales, so we end up with a maximum of three prices per product-store-day. Every day we extract data on approximately 10 million store-products across the country.

Our data set has advantages and disadvantages relative to more common scanner price data. There are two main disadvantages. We do not observe prices for grocery stores that are not part of large companies (i.e., annual sales over approximately 50 million U.S. dollars).[4] More

[2] An additional update to fix errors is allowed until 10AM.

[3] We have sales data since mid-August 2016. Around 3.4% of products have sales available to everyone. After experimenting with the data, we believe that these are typically unique per store. However, there may be discounts (of different sizes) for users of different credit cards in the same day. Approximately 43.8% of products have at least one of this types of discounts. In such cases, it seems that the one with the largest discount is reported.

[4] According to survey information available for 2012-2013 (*Encuesta Nacional de Gastos de Hogares, ENGHo*), our data should include between 50 and 85% of the grocery sales in Argentina. In that year, grocery

importantly, we do not have purchase quantities or individual product weights. Therefore, our empirical analysis assigns equal weight to each product-store included.

Balancing these disadvantages, this data has several advantages. First, scanner price data is not easily available in developing countries, so our data helps fill this gap. Being Argentina a high-inflation country (about 30% in 2016), with the expectation that inflation will be reduced in the following years (an inflation target of the Central Bank of about 5% for 2019), also provides an interesting scenario. Moreover, having daily (instead of weekly or monthly) price data for all products (not just the ones being sold or bought) is an advantage. Knowing each store's chain provides us with new information that has not widely exploited before. Similarly, our data has precise location information on each store (not just zip codes), so it potentially allows us to create interesting measures of distance to competition, among others. Finally, we are able to identify both the list price and (possibly many) sales prices, which can be important when describing retailers' pricing strategies.

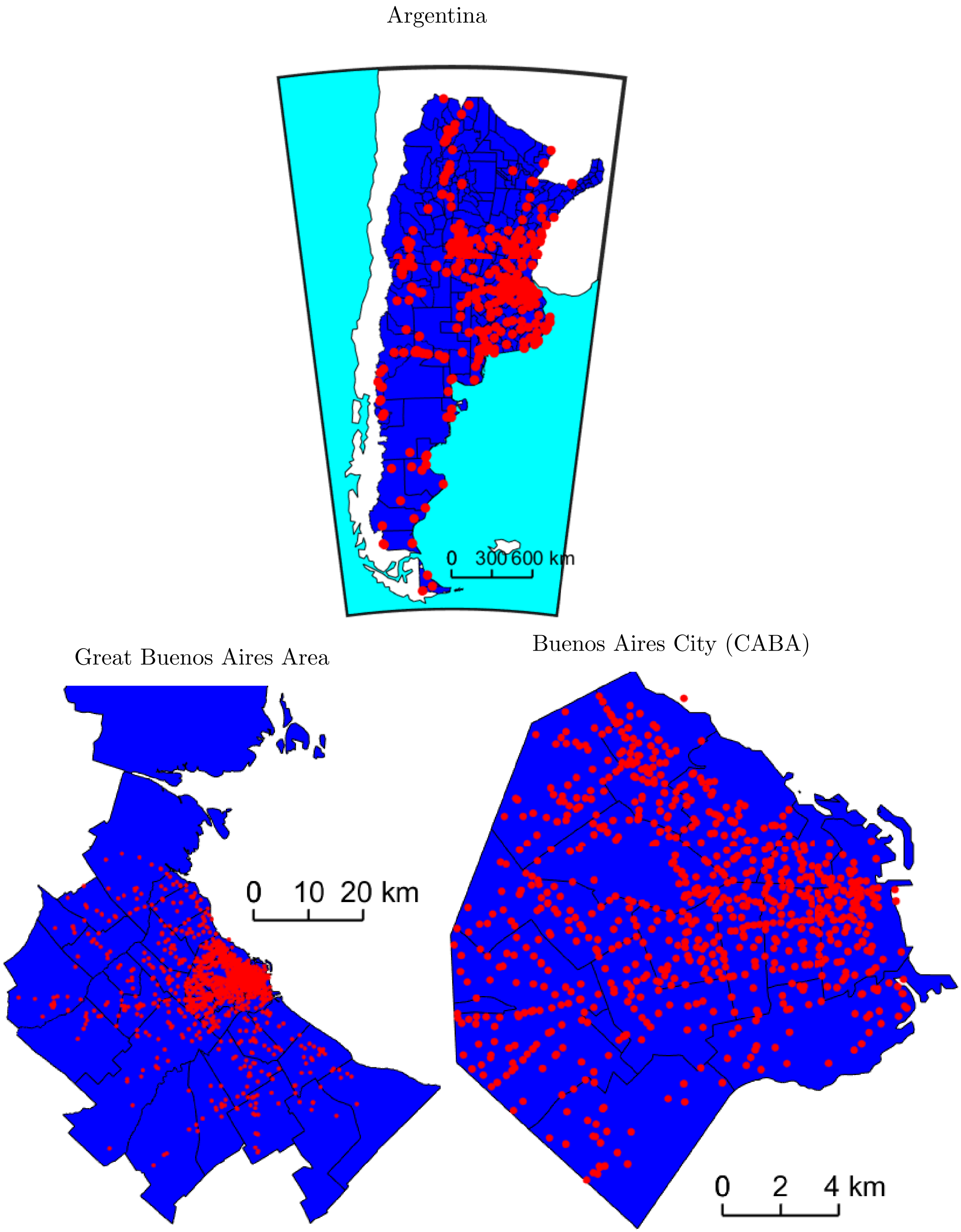
3.1 Descriptive Statistics

Figure 2 shows all the stores included in the data. Given that most stores are concentrated in the Buenos Aires area, the two bottom figures show in more detail Great Buenos Aires (GBA) and Buenos Aires City (CABA).[5] Given our interest in describing prices in a particular market, we choose CABA as our local market of analysis.

sales corresponded to approximately 33% of households' expenditures.

[5] Argentina has a population of about 40 million people. In GBA, the population is about 12 million and in CABA it is about 3 million. The area of CABA is 203 km^2. As a reference, CABA is about twice as large as Manhattan, both in population and area.

Figure 2: **Stores included**.



Source: Precios Claros.

We limit our attention to products with reported categories. After focusing on CABA, we are left with 790 stores organized in 5 chains. We clean the data such that we keep products that are commonly available across stores (solve by more than 500 stores), which is common in the literature (e.g., Kaplan, Menzio, Rudanko, and Trachter, 2016). Table 1 shows the characteristics of the sample before and after this procedure. Focusing on goods widely sold reduces the number of products from 49,882 to 2,794. Many goods are either sold by only chain (e.g., chain brands) and are therefore eliminated.[6] Importantly, even though the number of products is reduced by around 95%, the observations are reduced by only 78%. The products kept are the ones more common across stores, and hence have larger number of observations. Before doing the sample selection, each product was sold on average in 137 stores. After, this number increased to 661—84% of the stores in the sample. Finally, the last panel shows some characteristics of the products before and after cleaning. The average price of the products is around 20% (0.6 U.S. dollars) lower in the selected sample. More importantly, the average price dispersion—the cross-sectional standard deviation of the prices at which the same product is sold in the same day and city—in the initial and final samples remains almost constant.

Table 1: **Sample Selection**.

	Before	**After**
Number of chains	5	5
Number of stores	790	790
Number of products	49882	2794
Number of days	279	279
Number of observations (M)	1352	304
Products per store	8681	2336
Products per chain	23734	2541
Store per chain	158	158
Store per product	137	661
Average price (AR $)	49	40
Price dispersion	6.4%	6.7%

Source: Precios Claros, list prices. Note: Price dispersion refers to the average standard deviation of log-standardized-prices. This measure is explained in detail in the main text.

Given the differences in inflation levels between Argentina and the U.S., it is interesting that we find price dispersion in our data to be 6.7%, half of the one found by Kaplan, Menzio, Rudanko, and Trachter (2016) for the U.S. (15.3%). In addition to differences steaming from the economic

[6]It is also possible that some observations have misreported information, which implies that they are less likely to be common across stores. These observations would also be eliminated.

context, the main differences in the data are that we have daily posted list prices while they have quantity-weighted weekly prices. It is not clear what the effect of the data characteristics would be on price dispersion but in order to account for some of these differences we use the data including sale prices. In this case, we find that price dispersion increased to 9.6%, still below the one reported for the U.S.

4 Chains

In this section we study the role of chains on prices. We find that conditional on a product, there is little variation across stores of the same chain. However, we find large variation in relative prices between chains.

The number of stores by chains varies between 19 and 331. Table 2 shows some characteristics of each of the 5 chains in the sample. Importantly, some of them include different types of stores. The size of these stores (both physical and in the total number of products) also varies. For example, Chain I sells 1061 products whereas Chain III has 1770 products. We merge information on the location of stores with Census data in order to describe the characteristics of each chains' location. The row Education shows the average years of education across stores' locations for each chain. For example, this shows that Chain IV tends to locate its stores in areas from higher socio-economic groups than Chains I and II.

The second panel of Table 2 refers to average prices of each chain.[7] We sort chains by their expensiveness. Chain I is in general the cheapest, with a relative price 3.5% lower than the average. This contrasts significantly with Chain V which prices are on average 2.2% higher. The price ranking is associated with the stores' location characteristics, such that more expensive stores tend to locate in higher educated neighborhoods. However, this ranking hides significant variation across products. For example, the cheapest chain sets 5% of their prices at 5.6% above the market average. Similarly, the bottom 5th percentile of the most expensive chain is 2.9% below the average price.

[7]For each day, we define the relative prize as the log price minus the log of the mean price across stores for the same good. The relative price is defined as the average across time of the daily relative prices.

Table 2: **Chain Pricing Behavior**.

	I	**II**	**III**	**IV**	**V**
Chain characteristics					
Types of stores	3	1	1	3	3
Number of products	1061	878	1770	1363	1612
Education	12.06	12.41	12.58	13.24	12.77
Prices					
Price rank	1	2	3	4	5
Relative price (%)	-3.5	-2.3	-1.4	1.5	2.2
By product					
Percentile 5	-14.6	-9.4	-8.3	-7.8	-2.9
Percentile 10	-10.7	-7.3	-6.3	-5.7	-1.1
Percentile 25	-6.6	-4.6	-3.5	-1.9	0.1
Percentile 50	-2.8	-1.9	-1.1	0.7	1.9
Percentile 75	0.0	-0.0	0.5	5.0	4.3
Percentile 90	3.2	2.0	3.3	10.1	6.5
Percentile 95	5.6	3.9	5.8	13.0	8.1
Dispersion					
Unique prices by product	1.69	2.68	1.06	3.32	3.53
Price dispersion	4.67%	2.81%	0.94%	3.57%	4.29%

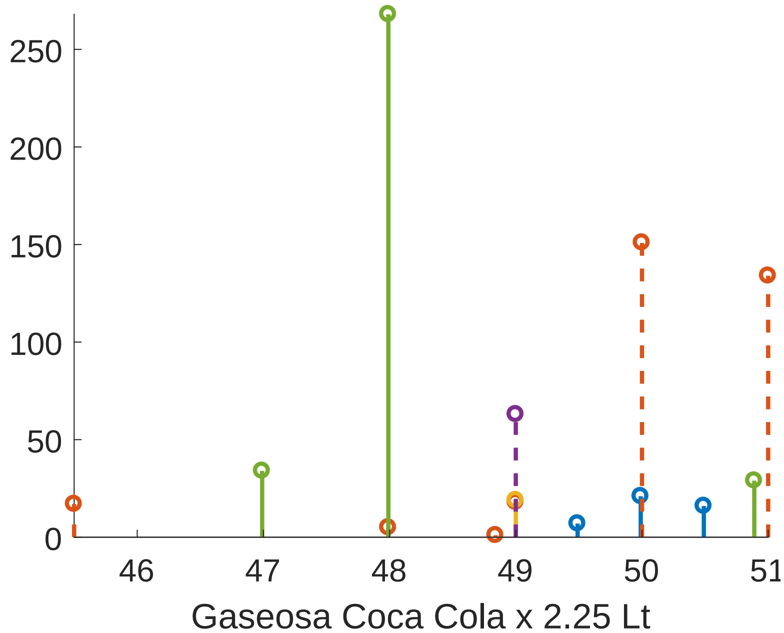
Source: Precios Claros, list prices. Note: Price dispersion refers to the average standard deviation of log-standardized-prices. This measure is explained in detail in the main text.

4.1 Price Bunching

To obtain some intuition about prices within chains we use a case study of the product *Coca-Cola 2.25 Lt*. Figure 3 shows the distribution of prices for this product in a given date. Different colors are used to identify each chain. Note that prices are bunched in only a few values.[8] Moreover, conditional on a chain, we see between one and four different prices across all stores. Also, note that different chains choose the same price of $50.00 for some of their stores. Appendix B.2 repeats this exercise for other products.

[8] For Coca-Cola 2.25 Lt prices are $45.50, $46.99; $47.99; $48.84; $49.00; $49.49; $49.99; $ 50.00; $50.49; $50.88; and $51.00.

Figure 3: **Price Dispersion for Coca-Cola: Bunching**.



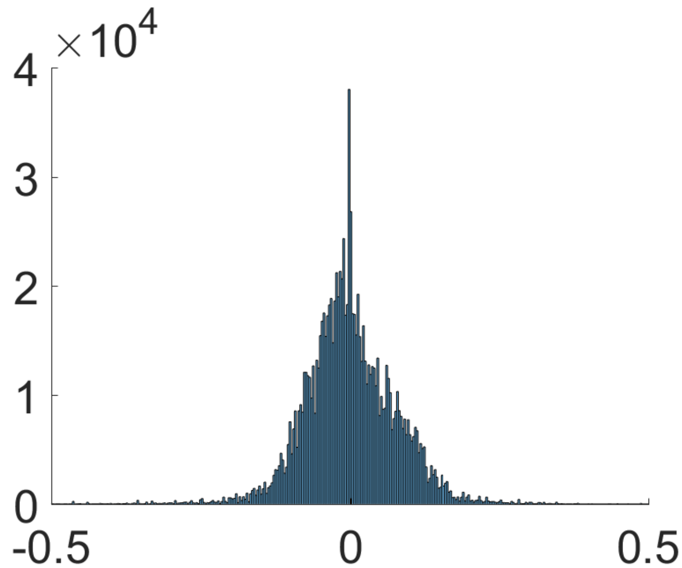
Source: Precios Claros. Each color refers to a different chain.

We formally show that price bunching is a general property of the data and not a particular case for Coca-Cola. The last panel of Table 2 points to the fact that product prices are almost unique within chains. The average number of unique prices for each good across stores is between 1 and 3.5 for all chains. It is important to note that chains with over 3 unique prices also have 3 types of stores. Moreover, table 1 showed that the price dispersion in the whole sample is 6.7% while price dispersion within chains is smaller, between 0.9% and 4.7%. If we further control for store type within chains the price dispersion is even smaller.

5 Price Dispersion

Recent literature has highlighted that price dispersion is a prevalent characteristic in many markets: The same product (UPC bar code) is sold at different prices by various stores in the local market and time period. Figure 4 shows that the distribution of relative prices for all the products is bell-shaped. However, Table 2 showed that prices are bunched within chains, i.e., the average number of unique prices for each product is approximately two per chain (as shown in the case study of Figure 3). Moreover, Table 2 also showed that there is significant variation in the relative price chains set for different products. These two facts suggest that it is these variation in average relative prices between chains that creates the smooth bell-shaped distribution of relative prices. In this section, we test this idea more formally.

Figure 4: **Relative Price Dispersion**.



Source: Precios Claros.

5.1 Statistical model

Understanding the origin of this price dispersion is important to understand stores' price setting as well as consumers' choices. (Kaplan, Menzio, Rudanko, and Trachter, 2016) highlights that a large share of the price dispersion is given by each store selling different sets of goods cheaper while charging similar prices on average. This situation suggests that an information problem might make consumers buy in a store selling goods more expensively since it is costly (or not possible) to get to know other stores' prices. Based on the evidence presented in Sections 4 and 6, we expand on this literature by introducing a new source of information: Chains.

We use two statistical models to do a variance decomposition of prices and formally highlight the role of chains behind price setting. First, we propose that $p_{g,s,c}$, the log-price of product (or good) g in store s of chain c, can be summarized by a product fixed-effect α_g, a chain fixed-effect β_c, a chain-product fixed-effect $\gamma_{g,c}$, and a residual $\epsilon_{g,s,c}$. The variation in $\epsilon_{g,s,c}$ is coming from different stores of the same chain setting different prices for the same product.

$$p_{g,s,c} = \alpha_g + \beta_c + \gamma_{g,c} + \epsilon_{g,s,c} \tag{1}$$

We refer to this model as "Chain-Product Model." We implement this analysis separately for each day, so the variation studied here is not related to prices changing over time—and we do not need to control for time factors. In our estimation, we assume that the conditional mean $\mathbb{E}\left[\beta_c + \gamma_{g,c}|g\right] = 0$, such that α_g absorbs the average price effect. This standardizes prices, facilitating the comparison of prices of different goods which may be more expensive due to their characteristics (e.g., 2.25 liter bottle of *Coke* vs 750 milliliter bottle of *Pantene* shampoo).[9] We also assume that $\mathbb{E}\left[\gamma_{g,c}|c\right] = 0$, such that β_c absorbs the average chain effect. This controls for some chains being on average more expensive, possibly due to their particular amenities. These assumptions simplify the estimation which is particularly important given the size of our sample and guarantee that covariance terms are zero. The estimation of α_g, β_c, and $\gamma_{g,c}$ can be done by conditional sample means:

$$\begin{aligned}
\hat{\alpha}_g &= \frac{1}{N_g} \sum_{s,c} p_{g,s,c} \\
\hat{\beta}_c &= \frac{1}{N_c} \sum_{g,s} \left(p_{g,s,c} - \hat{\alpha}_g\right) \\
\hat{\gamma}_{g,c} &= \frac{1}{N_{g,c}} \sum_{s} \left(p_{g,s,c} - \hat{\alpha}_g - \hat{\beta}_c\right) \\
\hat{\epsilon}_{g,s,c} &= p_{g,s,c} - \hat{\alpha}_g - \hat{\beta}_c - \hat{\gamma}_{g,c}
\end{aligned}$$

where (with a slight abuse of notation) N_g refers to the number of store-chains selling good g, N_c the number of price observations (i.e., good-stores) of chain c, and $N_{g,c}$ the number of stores selling good g in chain c.

In order to facilitate comparison with the literature, we follow Kaplan, Menzio, Rudanko, and Trachter (2016) and introduce a second model that controls for store fixed-effects without allowing for chain-product effects. We refer to this model as "Store Model." In this case:

$$p_{g,s,c} = \alpha_g + \phi_s + \eta_{g,s,c} \tag{2}$$

Once again we assume that $\mathbb{E}\left[\phi_s|g\right] = 0$ to simplify the estimation and avoid introducing covariance terms. In this model, the variation in $\eta_{g,s,c}$ comes from different stores (of any

[9] This is equivalent to analyzing "relative" prices as is done in Kaplan, Menzio, Rudanko, and Trachter (2016).

chain) setting different prices for the same product. These leads to the following estimates:

$$\hat{\phi}_s = \frac{1}{N_s} \sum_g (p_{g,s,c} - \hat{\alpha}_g)$$

$$\hat{\eta}_{g,s,c} = p_{g,s,c} - \hat{\alpha}_g - \hat{\phi}_s$$

where N_s refers to the number of products sold in store s.

We have two alternative variance decompositions, one for the "Chain-Product Model" and one for the "Store Model". We abstract from the price variation due to product characteristics α_g, we study dispersion in relative prices. In the Chain-Product Model we decompose relative price variation in a chain component, a chain-product component, and the residual:

$$\underbrace{\text{Var}\left(p_{g,s,c} - \hat{\alpha}_g\right)}_{\text{Relative Price}} = \underbrace{\text{Var}\left(\hat{\beta}_c\right)}_{\text{Chain}} + \underbrace{\text{Var}\left(\hat{\gamma}_{g,c}\right)}_{\text{Chain-Product}} + \underbrace{\text{Var}\left(\hat{\epsilon}_{g,s,c}\right)}_{\text{Residual}}$$

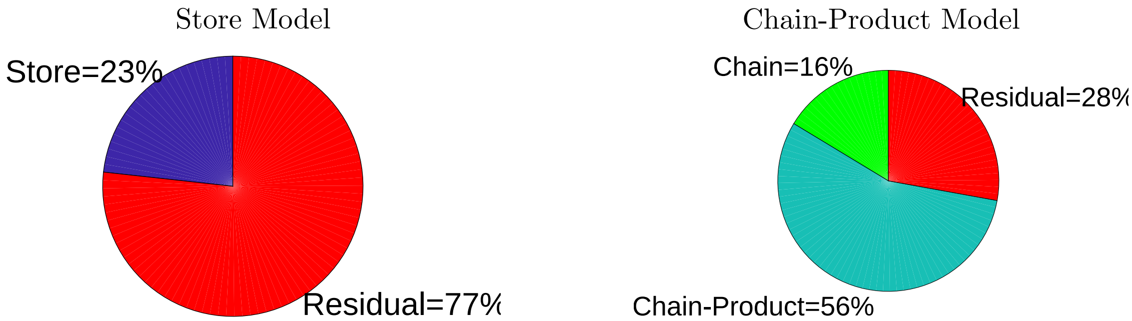
In the Store Model, we decompose relative-price variation into a store component and a residual component:

$$\underbrace{\text{Var}\left(p_{g,s,c} - \hat{\alpha}_g\right)}_{\text{Relative Price}} = \underbrace{\text{Var}\left(\hat{\phi}_s\right)}_{\text{Store}} + \underbrace{\text{Var}\left(\hat{\eta}_{g,s,c}\right)}_{\text{Residual}}.$$

5.2 Estimated Price Dispersion

The left chart of Figure 5 shows that our findings using the Store Model are similar to Kaplan, Menzio, Rudanko, and Trachter (2016). The share of price variation explained by stores is relatively small. Only 23% of price variation can be explained by some stores being more expensive in general. Most of the price variation (77%) is explained by some products being cheaper and others being more expensive in different stores. Based on similar results, Kaplan, Menzio, Rudanko, and Trachter (2016) propose that the problem customers are facing is one of limited information. Since it is hard to know the prices of hundreds of stores, individuals can only buy from the stores for which they know prices.

Figure 5: **Price Dispersion: Variance Decomposition**.



Source: Precios Claros.

Table 2 showed that prices are almost unique within chains, which suggests that it is not stores, but chains themselves that set most of the price variation. Discrimination of prices across stores of the same chain seems rather minimal. Using our alternative Chain-Product Model, the variation left in the residual is now given by different prices that chains set for the same products across their different stores. The right chart of Figure 5 shows that 16% of price variation is driven by some chains being more expensive than others in general. Once we control for average prices of products by chain, 72% (16% + 56%) of the price dispersion is explained. In Table 3 we show that extending the model to allow for category effects implies that the average price of categories by chain explains 29% of price variation.[10] Therefore, in line with the previous evidence in Table 2, pricing policies at the chain (not store) level seem to be the first order drivers of dispersion.

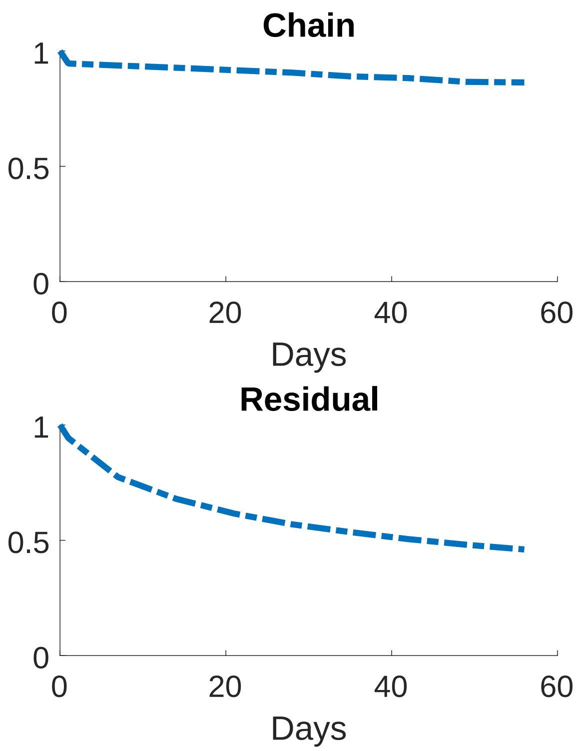
5.3 Persistent Price Dispersion

These findings have important implications for understanding price setting behavior and how consumers' make shopping choices. If most of the variation is determined at the chain level, the evidence supporting an information problem is reduced. Recall that there are 790 stores but only 5 chains. Knowing only a few sources of prices may be enough to significantly reduce information problems so the dispersion may need to be explained in a different way. One concern is that it might be the case that daily prices are mostly defined by chains, but these change very frequently over time. This could also introduce information problems, since the information obtained from shopping (or checking prices) in the past may not be informative of future prices. We show that these does not seem to be the case.

[10]See Section 7.3 for details on the Chain-Category-Product model.

We evaluate how persistent relative prices are by looking into the autocorrelation of the components of price dispersion. Figure 6 shows that for the Chain-Product Model these components are very persistent.[11] For a two-months window, the autocorrelation of the Chain component is approximately 0.9 and for Chain-Product this is closer to 0.6.

Figure 6: **Price Dispersion Persistence: Chain-Product Model**.



Source: Precios Claros, list prices.

We estimate an autoregressive process of order one at weekly frequency on these components. Results are gathered in Table 3. The different components of price dispersion are estimated to be highly persistent both in the Store and Chain-Product model. For example, the persistence coefficient is 0.98 for the chain component, implying a half-life of approximately 10 months. For the Chain-Product component the persistence coefficient is 0.91—equivalent to a half-life of over 7 weeks. In other words, if a chain prices a product 10% below the average in a given day, we expect this same chain to price it 5% below the average after 7 weeks.

[11] Appendix B shows similar results for the Store Model.

Table 3: **Price Dispersion: Persistence**.

	Variance Share	**Persistence (Weekly)**	**Shock Variance (x1000)**
Store Model			
Store	23.3	0.987	0.0290
Residual	76.7	0.900	0.6057
Chain-Product Model			
Chain	16.3	0.984	0.0198
Chain-Product	55.8	0.909	0.7546
Residual	27.9	0.901	0.2104
Chain-Category-Product Model			
Chain	16.3	0.984	0.0198
Chain-Cat3	13.0	0.907	0.3011
Chain-Cat3-Product	42.8	0.904	0.6442
Residual	27.9	0.901	0.2104

Source: Precios Claros, list prices.

Our results from the Chain-Product Model suggest that information problems may not be the first order element behind price dispersion. Since there are few (5) chains and these prices are persistent over time, knowing where to buy frequently-bought products (as groceries usually are) cheaper does not seem as difficult as the Store Model suggested. Even though information problems may still be a driver for price dispersion, another element is needed help explain how the results of Chain-Product Model are an equilibrium outcome.

6 Price Changes

This section studies the intensive and extensive margin of price changes. First, we verify that those moments are in line with previous empirical findings for countries with high inflation. We then show that there is large level of synchronization in price changes across stores of the same chain which reinforces the idea that chains are largely responsible for setting prices.

Table 4 shows estimates of typical moments related to price changes in our data—restricting our analysis to list prices only. The difference with previous estimates (e.g., Alvarez, Beraja, Gonzalez-Rozada, and Neumayer, 2016) is that we compute price changes for list prices at daily frequency rather than transaction prices at weekly or monthly frequency. The first panel shows that 3.5% of prices are changed every day, with approximately 2/3 of these changes being price increases and 1/3 being decreases.[12] Note that almost 70% of stores change at least one product's price every day. Among these stores, approximately 4.5% of prices are changed. This is above the unconditional share of price changes, suggesting that stores tend to group price changes rather than distribute them uniformly over time.

This table also presents evidence of price-changes synchronization. Midrigan (2011) highlights that price changes tend to occur at similar times for products of the same category in U.S. This is also true in our data. Among products that change prices, we observe that almost 25% of other products from the same level-3-category (the most narrowly defined) change prices in the same store. We notice however that price-change coordination seems stronger across chains than categories. Among products that change prices, we observe that 38.4% of other stores in the same chain change the price of the same product in the same day. The dispersion of these price changes is 2%, approximately one-sixth of the unconditional dispersion of price changes. Moreover, if we focus only on stores of the same type within the chain, the share of stores that change prices increases to almost 62%, with a dispersion of these changes of 1%. This evidence suggests that chains coordinate their price changes across stores.

The second panel of Table 4 focuses on the intensive margin of price changes. The average size of log-price changes is 2.1%, but this is actually driven by an average increase of 9.3% and an average decrease of almost 9.7%, with an average standard deviation of these changes of almost 12.6%. The numbers on the share of stores changing prices and average size of changes are in line with the evidence on countries with similar inflation rates (Alvarez, Beraja, Gonzalez-Rozada, and Neumayer, 2016). Figure 7 shows the histogram of the price changes in our dataset.

Finally, it will be useful for future analysis to introduce a single measure that combines the evidence on the intensive and extensive margins. The standard deviation of absolute price changes (including cases where this change is zero) increases both with the share of products changing prices as well as with the average size of those changes. We find this measure to be equal to 2.2% in our data.

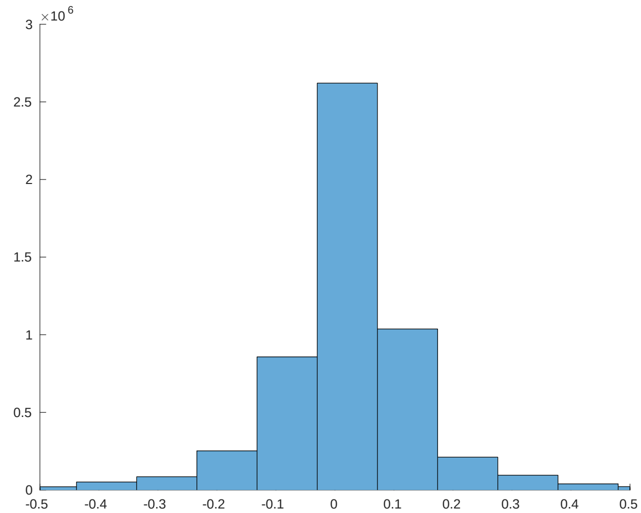
[12] Recall that inflation during this period is estimated to be approximately 30%.

Table 4: **Extensive and Intensive Margins of Price Changes**.

Extensive margin	
Price change	3.47%
Price increase	2.17%
Price decrease	1.31%
Stores that change prices	70.90%
Price changes by store	4.42%
Chains that change prices	81.58%
Price changes by chains	3.66%
Synchronized Changes: Conditional on product's price change	
Changed other products of same category, store level	24.81%
Changed other products of same category, chain level	11.30%
Changed in other stores of same chain	38.42%
Dispersion of % change	0.02
Changed in other stores of same type and chain	61.84%
Dispersion of % change	0.01
Intensive margin	
Size of price change	2.10%
Price increase	9.27%
Price decrease	-9.65%
Absolute price	9.47%
Std. deviation of price change	12.59%
Extensive and Intensive margins	
Std. deviation of abs. price change (incl 0)	2.22%

Source: Precios Claros, list prices. Statistics are in daily frequency. For example, 3.47% of prices are changed everyday. "Price changes by store" refers to the share of prices that were changed by stores that changed the price of at least one product.

Figure 7: **Price Changes: Histogram**.



Source: Precios Claros, list prices. Figure shows the distribution of (daily) price changes among products that changed prices.

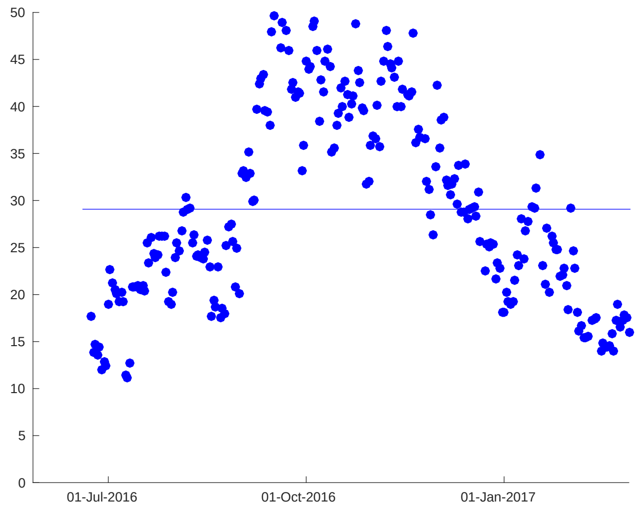
6.1 Inflation

One of the government's objective of setting up this online resource of prices was to reduce inflation. We use the data we scraped to estimate inflation: every day we compute average monthly price changes and extrapolate to calculate annual inflation.[13] Figure 8 shows this estimation. Inflation seems to have actually increased around September 2016, but since November 2016 it seems to have initiated a reduction. Our mean estimated inflation is 30%, which is close to the official estimation (for the same period and expenditure category). If inflation is actually reduced, it will be interesting to compute other price statistics and see how these change with inflation—something that is not possible in scanner data from countries with low and stable inflation.[14]

[13] One important limitation already mentioned is that we don't observe quantities. Therefore, all products received equal weight. However, a priori it is not obvious if this measure has an upward or downward bias.

[14] We will take this route on a companion paper once we have enough variation on the inflation level.

Figure 8: **Inflation Estimation**.



Source: Precios Claros, list prices. Estimation is based on daily frequency of monthly changes of prices. This is then extrapolated to report annual inflation estimation.The solid line shows the average.

7 Variation Across Products' Categories

In this section we exploit variation across products' categories to study price changes, price dispersion, and price correlations. The database has a category tree that groups the products into different categories. For the analysis in this section we use the broader category group which splits the sample into 9 categories: (1) Frozen food, (2) Grocery, (3) Alcoholic beverages, (4) Non-alcoholic beverages, (5) Baby supplies, (6) Fresh food, (7) Household supplies, (8) Pet supplies, and (9) Personal Care.

7.1 Price Changes

We estimate the distribution of price changes across different product categories and find that the intensive and extensive margins of price adjustments are heterogeneous. Moreover, price changes within categories are more similar than across categories.

The intensive and extensive margins of price adjustments are heterogeneous across categories. Columns two to five of table 5 show the share and size of price changes at daily frequency, split by price increases and decreases. The last row shows the moments for all the products in the market. The other rows show the deviation for each category from the market value to highlight the difference between them. For example, on average 2.17% of products increased prices but Pet supplies (category 8) had only 1.6% (2.17% - 0.57%) share of price increases. Similarly, the average size of price increases is 9.27%, but for Pet supplies the average size is 27.68%.

The unconditional standard deviation of price changes is 9.37%, as shown by column six of Table 5. However, this variation is smaller once we focus on changes within categories. For example, Baby (category 5) and Pet supplies (category 8) have one-third smaller standard deviation of price changes. The last column summarizes the information from the intensive and extensive margins by computing the standard deviation of price changes including observations with no changes (i.e., zero change). This variation of price changes is also generally smaller within categories than in the unconditional sample.

Frequency and size of price changes are important to understand the real effects of monetary policy according to both state and time dependent models (e.g., Alvarez, Lippi, and Passadore, 2016). The average across all goods of these moments is usually used to identify the transmission of monetary policy shocks to the real economy. However, we find that there are significant differences in this moment across product categories, which suggests that the real effect may differ across different sectors. The standard deviation of price changes is also important to estimate these models. We find that the variation within categories is up to one-third smaller than in the unconditional sample, affecting the real effects of monetary policy.

Table 5: **Price changes by categories**.

Category	**Price Increase**		**Price Decrease**		**SD Abs. Change**	
	Share	**Change**	**Share**	**Change**	**Changers**	**All**
Frozen food	0.23%	3.49%	0.11%	-3.44%	-1.05	0.03
Grocery	0.06%	-0.08%	-0.05%	-0.56%	-0.27	-0.09
Alcoholic beverages	-0.44%	2.67%	-0.44%	-2.94%	-0.66	-0.50
Non-alcoholic beverages	0.19%	0.26%	0.13%	-0.09%	-1.63	0.00
Baby supplies	-0.03%	1.72%	0.10%	-1.41%	-2.94	-0.51
Fresh food	0.13%	0.60%	-0.04%	-1.13%	-1.80	-0.29
Household supplies	-0.22%	-0.11%	0.02%	0.54%	-1.24	-0.31
Pet supplies	-0.57%	18.41%	-0.06%	-19.27%	-2.86	-1.12
Personal care	-0.11%	-0.25%	0.11%	-0.47%	-0.55	-0.18
All	2.17%	9.27%	1.31%	-9.65%	9.37	2.22

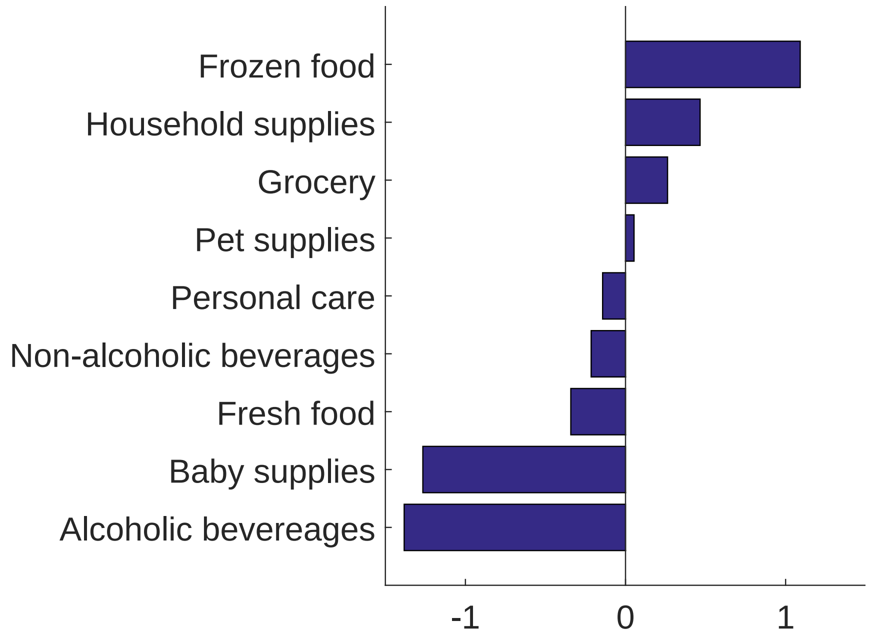
Source: Precios Claros, list prices. Statistics are in daily frequency. Values for each category are shown as deviations from the average in the whole sample, shown in the last row.

7.2 Price Dispersion

Relative price dispersion also varies across categories. Recall that the price dispersion is 6.71% for the whole sample. Figure 9 shows the heterogeneity between categories, as the difference between the price dispersion in each category and the one from the whole sample. For example, Frozen food shows the most dispersion (1.1 percentages point above the whole sample) while alcoholic beverages shows the least dispersion (1.4 percentage points below).

Under the lens of search models of price dispersion (e.g., Burdett and Judd, 1983), price dispersion is important to identify how captive consumers are. Our evidence suggests that frozen food or household supplies shoppers may be more captive than baby supplies or alcoholic beverages shoppers. However, consumers usually buy goods from different categories in the same shop visit so we now study how correlated relative prices are across categories.

Figure 9: **Price Dispersion Across categories**.



Source: Precios Claros, list prices. Values for each category are shown as deviations from the average in the whole sample.

7.3 Correlated prices

A large fraction of the relative price dispersion is explained by the chain-product interaction. A possible reason could be that each chain sets relative prices independently across products. Here we present evidence that this is not the case by looking at the correlation of relative prices across chains.

We extend the statistical model of Section 5.1 to introduce variation across categories. We propose that $p_{g,j,s,c}$, the log-price of product (or good) g of category j, in store s of chain c, can be summarized by a product fixed-effect α_g, a chain fixed-effect β_c, a chain-category fixed-effect $\delta_{j,c}$, a chain-category-product fixed-effect $\gamma_{g,j,c}$, and a residual $\epsilon_{g,j,s,c}$. The variation in $\epsilon_{g,j,s,c}$ is coming from different stores of the same chain setting different prices for the same product.

$$p_{g,j,s,c} = \alpha_g + \beta_c + \delta_{j,c} + \gamma_{g,j,c} + \epsilon_{g,j,s,c} \tag{3}$$

We refer to this model as "Chain-Category-Product Model." In our estimation, we assume that the conditional mean $\mathbb{E}\left[\beta_c + \delta_{j,c} + \gamma_{g,c}|g\right] = 0$, such that α_g absorbs the average price effect. We also assume that $\mathbb{E}\left[\delta_{j,c}+\gamma_{g,j,c}|c\right]=0$, such that β_c absorbs the average chain effect. Similarly, assume that $\mathbb{E}\left[\gamma_{g,j,c}|j\right]=0$, such that δ_j absorbs the average chain-category effect. These assumptions simplify the estimation which is particularly important given the size of our sample and guarantee that covariance terms are zero. The estimation can be done by conditional sample means:

$$\begin{aligned}
\hat{\alpha}_g &= \frac{1}{N_g}\sum_{j,s,c} p_{g,j,s,c} \\
\hat{\beta}_c &= \frac{1}{N_c}\sum_{j,g,s}\left(p_{g,j,s,c}-\hat{\alpha}_g\right) \\
\hat{\delta}_{j,c} &= \frac{1}{N_{j,c}}\sum_{g,s}\left(p_{g,j,s,c}-\hat{\alpha}_g-\hat{\beta}_c\right) \\
\hat{\gamma}_{g,j,c} &= \frac{1}{N_{j,g,c}}\sum_{s}\left(p_{g,j,s,c}-\hat{\alpha}_g-\hat{\beta}_c-\hat{\delta}_{j,c}\right) \\
\hat{\epsilon}_{g,j,s,c} &= p_{g,j,s,c}-\hat{\alpha}_g-\hat{\beta}_c-\hat{\delta}_{j,c}-\hat{\gamma}_{g,c}
\end{aligned}$$

We exploit the variation in the chain-category fixed effect $\delta_{j,c}$ to estimate the correlation of prices across categories.[15] For two categories $j_1 \neq j_2$ we exploit the variation across chains and estimate the correlation $corr\left(\delta_{j_1,c},\delta_{j_2,c}\right)$. Table 6 shows the matrix of correlations.

To understand the correlation matrix, we consider three illustrative examples with two chains. First, if prices are i.i.d. across categories, then the correlation is equal to zero. Second, if chains charge the same relative price across two categories, then the correlation between those two categories is equal to one. Third, if one chain charges one category expensive and the other cheap and the other chain does the opposite, the correlation is equal to minus one. We interpret values different from zero as an indicator that chains are not setting relative prices in an i.i.d. fashion but in a systematic way. Table 6 shows a large dispersion in coefficients with values between -0.89 for frozen food and grocery , and 0.74 for categories frozen food and non-alcoholic beverages.

Finally, we define an index of correlated pricing as the mean absolute correlation of price

[15]In this section we collapse all the time variation by looking at the average across time of $\hat{\delta}_{j,c}$. In Appendix B.1 we show that our results are robust to repeating the exercise at daily frequency, i.e., calculating the covariance each day.

Table 6: **Relative price correlation across categories**.

	1	2	3	4	5	6	7	8	9
1. Frozen foods	1.00	-0.89	0.46	0.74	-0.36	0.03	-0.85	-0.54	0.06
2. Grocery	-0.89	1.00	-0.53	-0.38	0.13	-0.21	0.71	0.54	-0.11
3. Alcoholic beverages	0.46	-0.53	1.00	0.25	0.58	-0.08	-0.72	-0.63	0.11
4. Non-alcoholic beverages	0.74	-0.38	0.25	1.00	-0.55	-0.04	-0.81	-0.18	-0.27
5. Baby supplies	-0.36	0.13	0.58	-0.55	1.00	-0.33	0.15	-0.43	0.43
6. Fresh foods	0.03	-0.21	-0.08	-0.04	-0.33	1.00	-0.13	0.67	-0.83
7. Household supplies	-0.85	0.71	-0.72	-0.81	0.15	-0.13	1.00	0.41	0.23
8. Pet supplies	-0.54	0.54	-0.63	-0.18	-0.43	0.67	0.41	1.00	-0.79
9. Personal Care	0.06	-0.11	0.11	-0.27	0.43	-0.83	0.23	-0.79	1.00

Source: Precios Claros, list prices.

dispersion across categories

$$\text{Mean Absolute Correlation}_j = \frac{1}{N_j}\sum_{\tilde{j}} \left| corr\left(\delta_{\tilde{j},c}, \delta_{j,c}\right)\right| \tag{4}$$

$$\text{Price-Correlation Index} = \frac{1}{N_j}\sum_{\tilde{j}} \text{Mean Absolute Correlation}_{\tilde{j}} \tag{5}$$

We find that the Price-Correlation Index is equal to 0.48. This estimate provides evidence that chains set prices across categories in a systematic way.

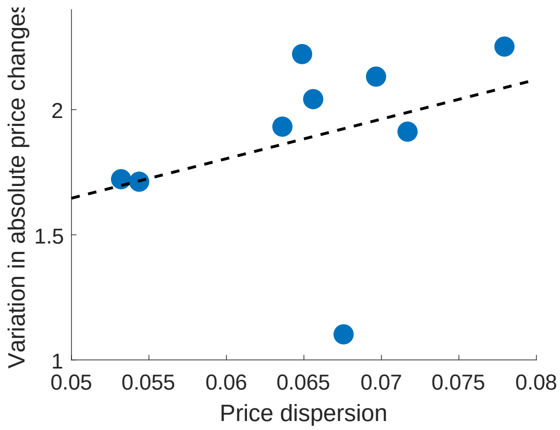
7.4 Covariances

We exploit the variation across categories to study the relationship between price dispersion, price changes, and mean absolute correlation. The left panel of Figure 10a shows that categories with higher price dispersion are associated with higher standard deviation of absolute price changes (including products that do not change prices). This suggests that categories associated with higher price dispersion are associated with higher share of prices changes and larger changes.

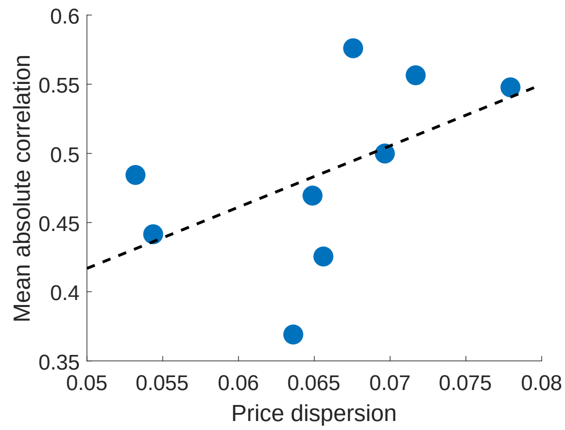
Next we study the relationship between price dispersion and correlated pricing. We use the mean absolute correlation for each category defined in Equation 4 . Figure 10b shows that categories with higher mean absolute correlation are associated with higher price dispersion. This pattern is in line with models in which price dispersion is generated by sellers setting negatively correlated prices.

Figure 10: **Variation across categories**

(a) **Price changes**.



(b) **Correlated pricing**.



Source: Precios Claros, list prices.

8 Conclusion

We create a new database of retail prices in Argentina with over 10 million observations per day to study micro-price statistics for a high-inflation country. Our main novel finding is that chains, rather than stores, explain most of the price variation. For example, 72% of the price dispersion can be explained by a chain-product fixed effect, leaving only 28% of the price variation to be explained by stores setting different prices within a chain. We also study how correlated relative prices are across categories and show that the mean absolute correlation of prices across categories is about 50% in our data, suggesting that relative prices move in systematic ways. Finally, we show that price changes, price dispersion, and price correlations are heterogeneous across product categories. More importantly, we find that categories with higher price dispersion are associated with larger price changes and higher price correlations.

In this paper we present the new data and document some empirical facts about prices. The richness of the data allows us to extend the analysis in several dimensions. For example, there is a large literature studying the effect of temporary sales (e.g., Kehoe and Midrigan, 2008; Alvarez and Lippi, 2016). As we observe both list and sales prices, our database can provide useful insights to test those theories. Similarly, Argentina provides a unique framework with an expected path of decreasing inflation. Hence, our data can contribute to the study of how micro-price statistics (particularly price dispersion) change with the level of inflation. We plan to study these extensions in companion papers.

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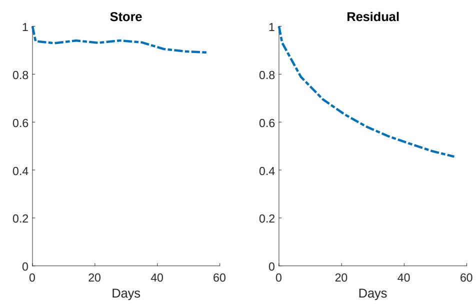
Appendix

A Additional results

B Price dispersion: Persistence of Store-Model

Figure 11 shows the autocorrelations for the Store Model.

Figure 11: **Price Dispersion Persistence: Store Model**.



Source: Precios Claros, list prices.

B.1 Price dispersion by categories

Table 7 shows the relative price correlation across categories for daily data and Table 8 shows the standard deviation.

Table 7: **Relative price correlation across categories: Daily data**.

	1	2	3	4	5	6	7	8	9
1	1.00	-0.56	0.26	0.29	-0.14	-0.03	-0.23	-0.65	0.06
2	-0.56	1.00	-0.27	-0.18	0.03	-0.19	0.21	0.61	-0.28
3	0.26	-0.27	1.00	0.20	0.34	-0.12	-0.15	-0.60	-0.05
4	0.29	-0.18	0.20	1.00	-0.37	-0.09	-0.18	0.23	-0.33
5	-0.14	0.03	0.34	-0.37	1.00	-0.19	-0.03	-0.60	0.17
6	-0.03	-0.19	-0.12	-0.09	-0.19	1.00	-0.27	0.54	-0.53
7	-0.23	0.21	-0.15	-0.18	-0.03	-0.27	1.00	0.47	-0.05
8	-0.65	0.61	-0.60	0.23	-0.60	0.54	0.47	1.00	-0.94
9	0.06	-0.28	-0.05	-0.33	0.17	-0.53	-0.05	-0.94	1.00

Source: Precios Claros, list prices.

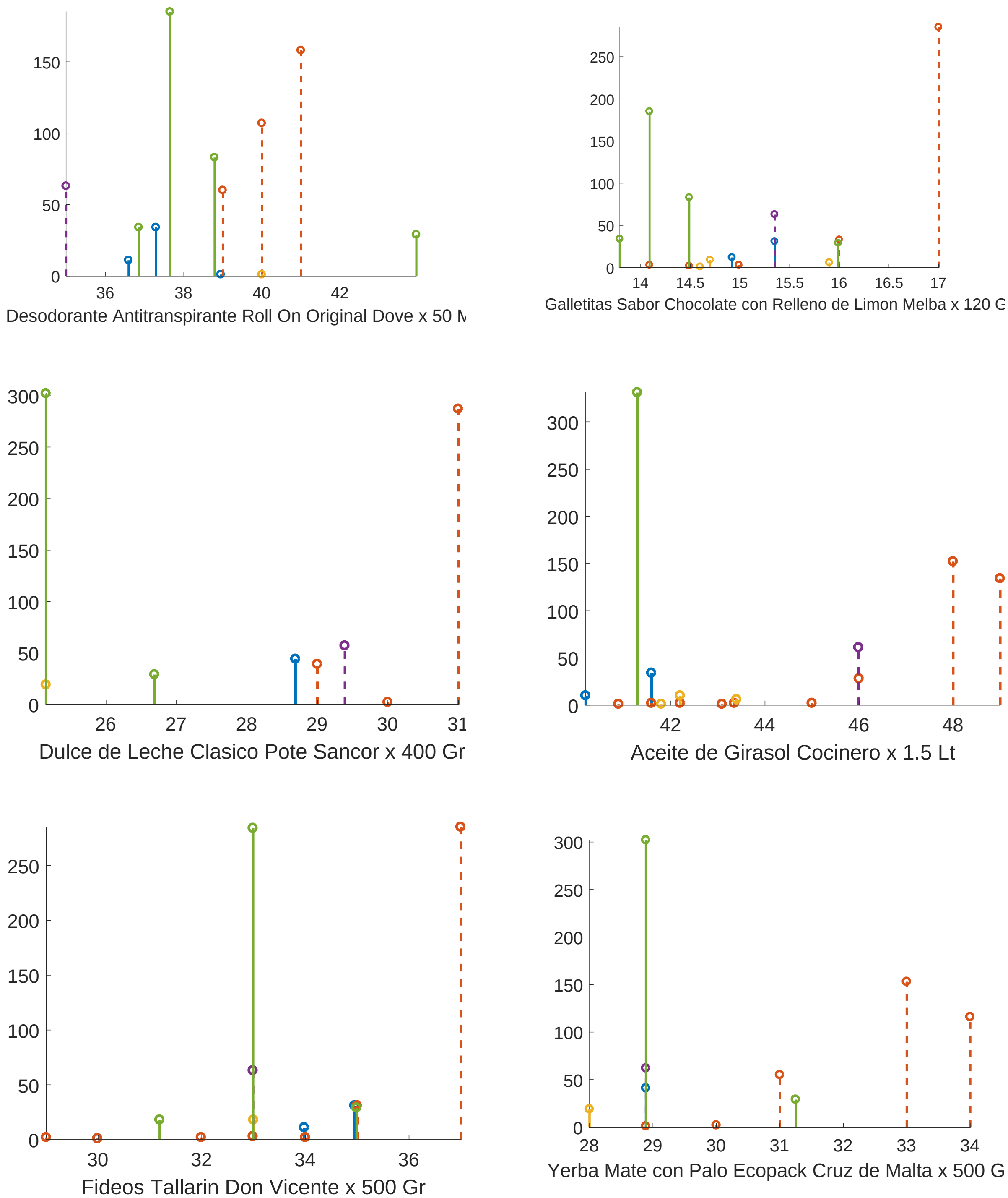
Table 8: **Relative price correlation across categories: Standard deviation of Daily data**.

	1	2	3	4	5	6	7	8	9
1	0.00	0.29	0.42	0.36	0.38	0.47	0.44	0.20	0.57
2	0.29	0.00	0.59	0.38	0.46	0.42	0.54	0.16	0.36
3	0.42	0.59	0.00	0.43	0.34	0.37	0.57	0.13	0.46
4	0.36	0.38	0.43	0.00	0.42	0.46	0.54	0.23	0.33
5	0.38	0.46	0.34	0.42	0.00	0.40	0.49	0.21	0.38
6	0.47	0.42	0.37	0.46	0.40	0.00	0.47	0.24	0.35
7	0.44	0.54	0.57	0.54	0.49	0.47	0.00	0.29	0.47
8	0.20	0.16	0.13	0.23	0.21	0.24	0.29	0.00	0.08
9	0.57	0.36	0.46	0.33	0.38	0.35	0.47	0.08	0.00

Source: Precios Claros, list prices.

B.2 Price dispersion: Examples

Figure 12: **Example of Price Dispersion**.



Source: Precios Claros.