Macroeconomic Implications of Uniform Pricing

Diego Daruich
University of Southern California

Julian Kozlowski
FRB of St. Louis

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Abstract

We compile a new database of grocery prices in Argentina, with over 9 million observations per day. We find uniform pricing both within and across regions—i.e., product prices almost do not vary within stores of a chain. Uniform pricing implies that prices would not change with regional conditions or shocks, particularly so if chains operate in several regions. We confirm this hypothesis using employment data. While prices in stores of chains operating almost exclusively in one region do react to changes in regional employment, stores of chains that operate in many regions do not seem to react to local labor market conditions. We study the impact of uniform pricing on estimates of local and aggregate elasticities in a regional model with uniform pricing. The estimated model predicts an almost one-third smaller elasticity of prices to a regional than an aggregate shock. This result highlights that some caution may be necessary when using regional shocks to estimate aggregate elasticities, particularly when the relevant prices are set uniformly across regions.

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1 Introduction

There is a growing and influential literature that uses regional variation to identify local elasticities (e.g., Mian and Sufi, 2011; Autor, Dorn, and Hanson, 2013), and then uses these local elasticities to understand the aggregate economy. We argue, however, that the presence of firms in multiple regions has important implications on how to use the regional variation to make inference about aggregate elasticities. In this paper we make three main contributions to understand what the presence of multi-region firms implies for macroeconomics. First, we introduce novel data from Argentina and show that there is uniform-pricing: multi-region chains tend to set the same prices across stores both within and across regions. Second, we show that prices tend to react relatively little to local conditions, particularly so for firms that operate in multiple regions. Finally, we build a model to understand the macroeconomic implications of uniform pricing. Our key finding is that consumption aggregate elasticities (i.e., to aggregate shocks) tend to be smaller than local elasticities (i.e., to local shocks), as prices react more to aggregate conditions when prices are set uniformly across regions. This result highlights that some caution may be necessary when using regional shocks to estimate aggregate elasticities, particularly when the relevant prices are set uniformly across regions.

Most empirical analysis about micro-price statistics use scanner price data from developed countries with low inflation. One contribution is the creation of a new database for daily posted grocery store prices in Argentina in a high-inflation context. Since May 2016, every day, stores have to report their offline prices (i.e., prices in the store) to the Argentinean government. The data is processed and posted online in an official price-comparison website, with the objective of providing information to consumers. We have about 9 million price observations per day, totaling about 5 billion observations, which allows us to have a large panel on chains, stores, products, and prices. Having daily posted prices is crucial for our objective of studying pricing strategies since we do not rely on average prices nor do we need to aggregate time periods (as in scanner data).

Our first empirical finding, using our new data, is that there is *uniform pricing*—i.e., conditional on a product, there is little variation in prices across stores of the same chain. There are three pieces of evidence consistent with this fact. First, even though chains have on average over 100 stores across the country, we find that, on average, there are less than 4 unique prices for each product-chain group. Second, price changes are also consistent with uniform pricing. Focusing on products that change prices in one store, we compute the probability that other stores change the prices of the same products on the same day. The probability is 5% for stores of *any* chain, but it increases to almost 30% when we focus on stores of the *same* chain.[1] Third, using a variance decomposition methodology, we find that around two-thirds of the relative price dispersion can be explained by chain-product fixed effects.[2] Hence, only

[1]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.

[2]This decomposition is done using relative prices in order to abstract from differences in product characteristics. For each product in a store an given day, we define a relative price as its log-price deviation from the average log-price across stores on that day.

one-third of the price variation can be explained by stores setting different prices within a chain.

Our second empirical finding is that prices tend to react relatively little to local conditions, particularly so for firms that operate in multiple regions. We use employment data at the province level as a proxy of local conditions. We find that prices in stores of chains operating almost exclusively in one region do react to local conditions, while stores of chains that operate in many regions do not seem to react to local labor market conditions. This result suggests that prices would not change with regional conditions or shocks, particularly so if chains operate in several regions (e.g., national chains or e-commerce) which can be important for the use of local elasticity estimates to predict aggregate elasticities.

Our third contribution is the study of the macroeconomic implications of uniform pricing for the effects of regional relative to aggregate shocks. We extend the model of heterogeneous regions of Bernard, Jensen, Redding, and Schott (2018) to uniform pricing and general equilibrium. Regions have three sources of heterogeneity. First, there is variation in size, which is mapped to population size, to study heterogeneous effects of regional shocks between small and large regions. Second, households have different preferences for sellers across regions, which generates variation on the sellers' market shares as in the data. Third, there are region-specific exports to generate regional (and aggregate) exogenous shocks.

We estimate the model to match the fact that firms operating mostly in one region react more to local shocks. Uniform pricing implies that consumption reacts less in response to an aggregate than to a regional shock because prices adjust more in response to aggregate shocks. The estimated model predicts an almost one-third smaller elasticity of prices to a regional shock than to an aggregate one. This result highlights that some caution may be necessary when using regional shocks to estimate aggregate elasticities, particularly when the relevant prices are set uniformly across regions.

There is substantial heterogeneity on elasticities across regions due to their sizes as well as the market structure. First, smaller regions have a smaller response to regional shocks because firms setting uniform prices assign less weight on their regional demand and marginal cost, so they react less to regional shocks. Second, when there are more national firms, prices react less to regional shocks because firms assign less weight to local demand. Uniform pricing also implies that regional shocks have spillover effects on other regions. As firms set the same price in all regions, shocks in one region lead to national price changes. Spillovers are heterogeneous depending on where the shock takes place. Bigger regions have a larger impact on prices, hence leading to larger spillover effects.

The rest of the paper is organized as follows. Section 2 discusses the literature. Section 3 introduces our novel price dataset and provides basic descriptive statistics. Section 4 provides our main empirical results regarding uniform pricing. The model and the implications of uniform pricing for consumers and firms are presented in Sections 5 and 6. Finally, Section 7 concludes. The Appendices contain additional details on the data and model.

2 Related Literature

This paper is related to several strands of the literature related to price-setting behavior and its macroeconomic consequences. First, there is an empirical literature on gathering new data on retail prices in developing countries. Cavallo and Rigobon (2016) provide a summary of this new research agenda. The novelty of our paper is that we obtain information on offline prices (i.e., prices in the store) instead of online prices as in previous research. Since February 2016, the Argentinean government has created a daily, national, publicly available report of prices (*Sistema Electronico de Publicidad de Precios Argentinos*). To the best of our knowledge, we are the first to collect and analyze this data. Alvarez, Beraja, Gonzalez-Rozada, and Neumeyer (2018) also study micro-price statistics for Argentina, but for a different period (1988 to 1997) and with a smaller sample.[3] 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 Neumeyer (2018) the average number of observations per month is about 81,000, whereas we have about 9 million observations per day. Similarly, they have information on 500 products, whereas we have four times as many products in our final sample selection.[4]

This paper is also part of a growing literature that studies price dispersion and uniform pricing. Kaplan, Menzio, Rudanko, and Trachter (2019) find that, in the US, most of the price dispersion is across stores that are equally expensive but set different relative prices. We show that this is true also in our data but argue that in fact most of the variation is at the chain rather than store level due to uniform pricing. Empirical studies find that many store characteristics are explained by chains. For example, Hwang, Bronnenberg, and Thomadsen (2010) find that assortment gets set at the chain level, and Hwang and Thomadsen (2016) find that a large fraction of the variation of brand sales across stores is also explained at the chain level.[5]We extend this evidence, showing that prices also seem to be defined at the chain level. Price variation between grocery stores of the same chain is relatively small. Using US data, Nakamura, Nakamura, and Nakamura (2011), DellaVigna and Gentzkow (2019) and Adams and Williams (2019) also show that uniform pricing strategies are common in the US.[6] Previous papers, however, used scanner

[3]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 Neumeyer, 2018).

[4]An important difference relative to Alvarez, Beraja, Gonzalez-Rozada, and Neumeyer (2018) for our purposes is that we are able to compare the same products (EAN barcodes) across stores, while they cannot precisely compare products across stores (since products are defined as narrow categories but without barcodes).

[5]Regarding price adjustments, Midrigan (2011) uses data on a single chain in the US 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*.

[6]Cavallo, Neiman, and Rigobon (2014), Cavallo (2018), and Jo, Matsumura, and Weinstein (2018) highlight a new type of price convergence, or uniform pricing, due to e-commerce. E-retailers typically have a single-price or uniform-pricing strategy independent of the buyer's location. Cavallo, Neiman, and Rigobon (2014) highlight that only 21 out of the top 70 US retailers (among those that sell online) potentially have prices that vary by ZIP code, and 13 of these 21 are grocery stores. Jo, Matsumura, and Weinstein (2018) show that the introduction of *Rakuten* (the largest Japanese e-retailer) has led to a reduction in price differentials between Japanese offline retailers (of potentially many chains). In the US, Cavallo (2018) shows that the introduction of Amazon has led to a reduction in price differentials as well, but his focus is on price dispersion

price data, which has the disadvantages of being at weekly frequency and of using transaction prices that mix temporary sales with list prices. A distinct feature of our data is that we observe daily list posted prices, which allow us to get a more precise measure of uniform pricing.

Our main contribution, however, is the study of the macroeconomic implications of uniform pricing. We study the impact of regional shocks on firms with different shares of local stores, with the novel finding that under uniform pricing and multi-region firms, consumption elasticities to local shocks tend to be larger than to aggregate shocks since prices adjust more with aggregate shocks. This result relates to the literature that compares local and aggregate fiscal multipliers. Nakamura and Steinsson (2014) find that uniform monetary and tax policies (across a nation) imply that local government expenditure multipliers will be larger than an aggregate multiplier—since the latter would lead to larger monetary and tax adjustments. Dupor and Guerrero (2017) highlight other potential sources of spillovers as movements in factors of production and trade in goods, among others. Differently from Nakamura and Steinsson (2014), Dupor and Guerrero (2017) find small spillovers, hence suggesting that differences between local and aggregate multipliers are not large. In line with our results, Beraja, Hurst, and Ospina (2016) also provide indirect evidence that local prices may not significantly react to local employment conditions, since they estimate the impact of state-level employment growth on state-level wages to be almost equal when using either real or nominal wages. Finally, also in line with our findings, Baker, Johnson, and Kueng (2017) find that prices at wholesale firms (which tend to be larger and more geographically spread) react much less to local sales tax changes than prices at retail firms (which tend to be smaller and more local).[7] To the best of our knowledge, however, we are the first to highlight that uniform pricing has important implications for the growing literature that estimates various elasticities with respect to regional shocks (e.g., Mian and Sufi, 2011; Sufi, Mian, and Rao, 2013; Dupor and Guerrero, 2017; Beraja, Hurst, and Ospina, 2016; Yagan, 2018; Sergeyev and Mehrotra, 2018; Stroebel and Vavra, 2019). To do this, our model introduces uniform pricing and general equilibrium forces to the model of heterogeneous regions of Bernard, Jensen, Redding, and Schott (2018). Uniform pricing strategies in an economy with multi-region firms implies that elasticities to local shocks are likely to be biased estimates of elasticities to aggregate shocks.

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

within locations of a single chain (i.e., Walmart).

[7] Gagnon and Lopez-Salido (2019) show that large localized demand shocks due to labor conflicts, population displacement, and weather events translate into minimal changes in local supermarket prices. Cawley, Frisvold, Hill, and Jones (2018) show that pass-through of a Philadelphia soda tax into supermarket prices was smaller at chain stores than at independent retailers.

have to report daily prices to the government 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 products as well. Large fines (of up to 3 million US dollars) are to be applied if stores do not report their prices correctly. Since May 2016, the official website www.preciosclaros.gob.ar has provided consumer-friendly access to this price information. On this website, after entering their location, consumers can search for stores and products and compare 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 March 2018.[8]

We obtain information on each store and product. For each store, we know its name (not just an identification code), its chain owner, the type of store, and its precise location (latitude and longitude). Chains may have different types of stores based on size or known under different names in the market. We do not know whether these different types of stores operate as different chains, so in some of our analysis we define "chains" as "chain-types". For each product (barcode), 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 the hair care and oral care categories. Finally, the third level of the hair care category includes the shampoos and conditioners categories.

The prices posted on the website are the prices of products available at each (offline) store. Given that some products have special sales, we sometimes have several prices for a good in a particular store on a given day. In such cases, we know all available prices. Some of these sales are available only to some consumers—typically a percentage discount for customers with a particular credit card or membership. Some of these sales, however, also refer to discounts available to all consumers—for example, two for the price of one. In addition to the mandatory list price, each store can report one of each of these two types of sale prices. Because we can differentiate these two types of sales, we end up with a maximum of three prices per product-store-day.[9] Overall, we have daily data on approximately 9 million product-store observations across the country.

Our dataset 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., those with annual sales over approximately 50 million US dollars). According to survey information available for 2012-2013 (*Encuesta Nacional de Gastos de Hogares*), our data should include between 50 and 85% of grocery sales in Argentina. For that time period, grocery sales corresponded to approximately 33% of households' expenditures. More importantly, we do not have purchase quantities or individual product weights. Therefore, our empirical analysis assigns equal weight to each product-store included in the analysis.

[8] Appendix A.1 shows how the website works. Appendix A.2 argues that the data represents the real prices in the stores.

[9] In this paper we focus on list prices but the results are robust to incorporating sales prices. In a companion paper, we study the sales data in detail. Around 3.4% of products have sales available to everyone, while 43.8% of products have sales for specific customers. Among the latter, stores can have multiple sales for different types of costumers, but it seems that the sale with the largest discount is reported on the website.

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. Also, because Argentina is a high-inflation (about 30% in 2016) country, it 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 been 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 1 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 Greater Buenos Aires (GBA) and Buenos Aires City (CABA).[10] We first describe prices in a particular local market, CABA, and then study the pricing evidence from all stores in Argentina.[11]

The data includes 2313 stores of 22 chains, with around 50 thousand products. This implies about 9 millions product-store observations per day for 584 days, totaling about 5 billion observations. In order to study price dispersion, we limit our attention to products that are widely sold, as is common in the literature (e.g., Kaplan, Menzio, Rudanko, and Trachter, 2019). In particular, we clean the data such that we keep products that are sold by at least two chains and present in more than 50% of stores in a given region (i.e., either CABA or Argentina). We also focus on products that are sold most of the time (i.e., we focus on product-store combinations present in over 50% of the weeks). We also drop products in the price-control program *Precios Cuidados*, as there is no dispersion on these prices.[12] Table 1 shows some descriptive statistics for the data before and after cleaning, for CABA and Argentina. The data cleaning process does not eliminate any store. Even though it does reduce the number of products studied by around 90-95%, the number of observations is reduced by only two-thirds. The products kept are the ones more common across stores and hence have a larger number of observations.[13] The number of stores per product increases by around 500%, hence allowing us to have enough information to describe price dispersion. Finally, the average prices of the products are around 25% 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 on the same day and in the same region—in the initial and final samples

[10] Argentina has a population of approximately 44 million people. GBA and CABA account for approximately one-third and one-tenth of the country's population, respectively. The areas of GBA and CABA are 3,830 and 203 km^2, respectively. As a reference, CABA is about twice as large as Manhattan, both in population and area.

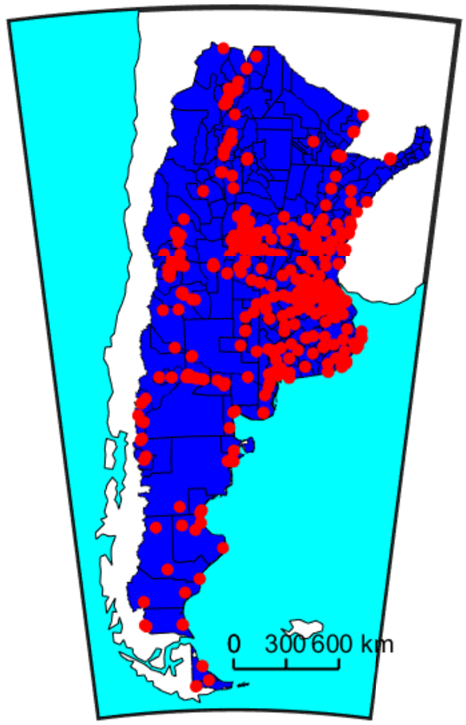
[11] Results are robust to choosing other cities (e.g., Cordoba).

[12] The program *Precios Cuidados* consists of price controls for about 300 products. See Aparicio and Cavallo (2018) for a study of this program.

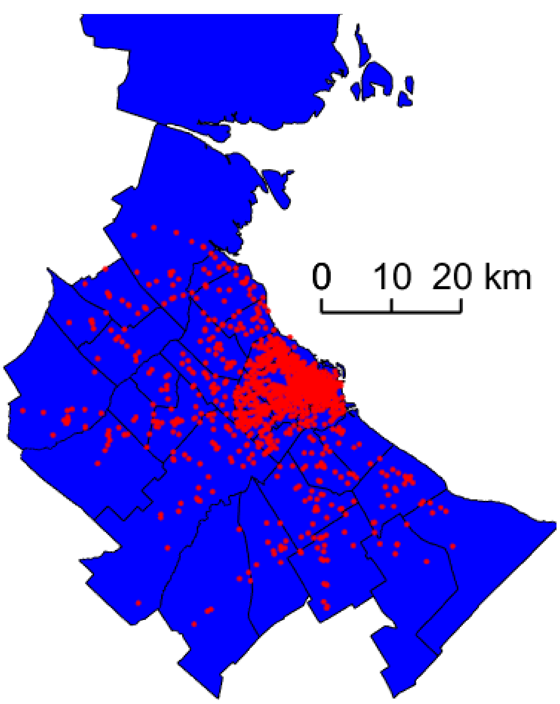
[13] It is also possible that some observations have misreported information, which implies that prices are less likely to be common across stores. These observations would also be eliminated.

Figure 1: Store Locations

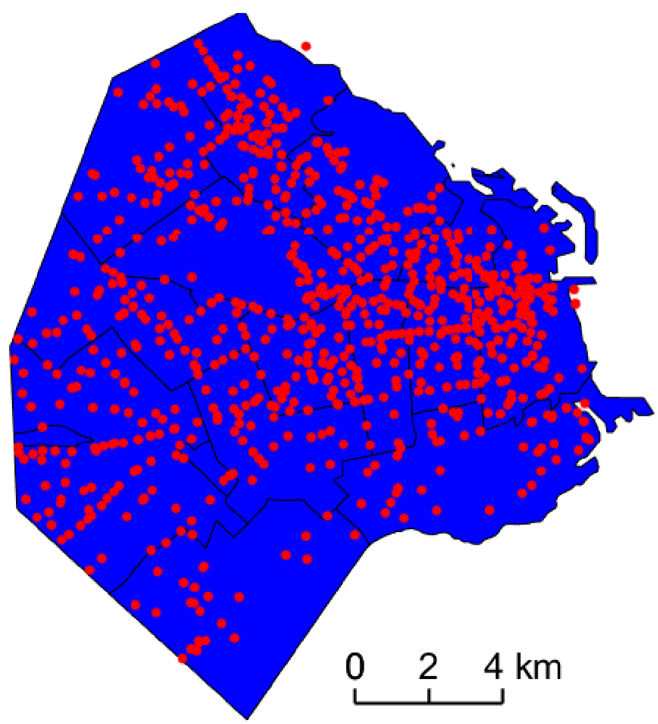
Argentina



Greater Buenos Aires (GBA)



Buenos Aires City (CABA)



Notes: Each dot refers to a store in the given region.

remains almost constant.

Table 1: Descriptive Statistics Before and After Cleaning

	CABA		Argentina	
	Before	**After**	**Before**	**After**
Number of chains	5	5	22	20
Number of stores	806	806	2313	2310
Number of products	26384	1805	50112	1773
Number of days	584	584	584	584
Number of observations per day (M)	2.69	0.90	9.14	2.37
Products per store	3537	1178	4243	1099
Products per chain	9876	1409	7553	1097
Stores per chain	158	158	123	125
Stores per product	102	489	183	1324
Average price (AR $)	61	46	61	45
Price dispersion (%)	6.5	7.0	10.0	9.7

Notes: Price dispersion refers to the average standard deviation of log-standardized prices. This measure is explained in detail in the main text.

Finally, we use the stores' locations to include two additional data sources. First, we use the the 2010 Census to incorporate characteristics such as education and employment of each store's location. Second, we use official data on regional employment to study the response of prices to local shocks.[14]

4 Empirical Results

In this section we study the role of chains (as opposed to stores) on prices. Recent literature has highlighted that price dispersion is a prevalent characteristic in many markets: The same product (defined by the EAN barcode) is sold at different prices by various stores in a local market and time period. We also find large variation in relative prices between chains. We find, however, that conditional on a product, there is little variation across stores of the same chain. We use the term "uniform pricing" to refer to this fact, i.e., that product prices do not vary within stores of a chain. The geographic boundary of a chain is not obvious, so we perform our analysis both using only Buenos Aires city data and using all Argentinean data. In both cases, we show that prices as well as price changes are remarkably similar for all stores within a chain.

We then introduce information on the characteristics of store locations and explore which chain characteristics correlate more with uniform pricing. Even though chains that operate in many provinces tend to display less uniform pricing, we find that the relationship is not strong, particularly when chains are

[14]Employment data is available at www.trabajo.gob.ar/estadisticas/oede/estadisticasregionales.asp.

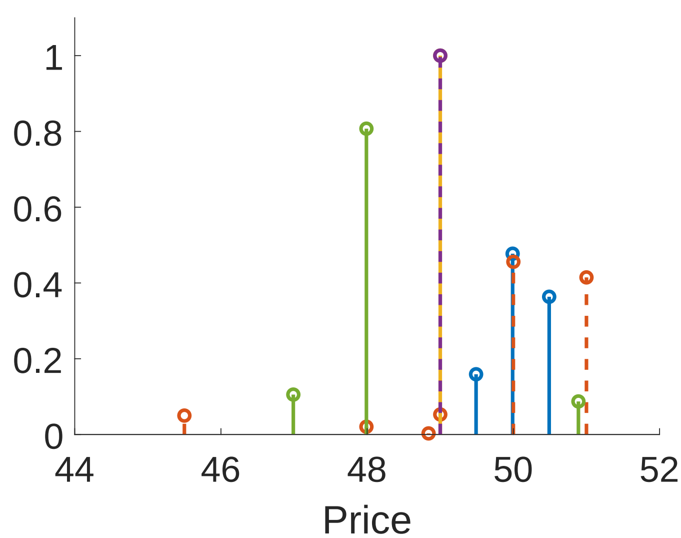
defined in a stricter way (i.e., according to chain-types). Chains may use subdivisions within the chain (which are fixed across time) to partially discriminate prices, but it seems that, once that is done, price differentiation between locations is not particularly strong.

One potential implication of uniform pricing is that grocery store prices would not change with regional conditions or shocks, particularly so if chains operate in several regions. We explore this hypothesis and show that prices in stores of chains that operate in many regions do not seem to react to local labor market conditions, while stores of chains operating almost exclusively in one region do react to local conditions.

4.1 Uniform Pricing

CABA has 806 grocery stores that belong to five different chains. The number of stores per chain varies between 17 and 340. The sizes of the stores, measured by the number of products sold, also vary between approximately 1,200 and 1,800. To obtain some intuition about prices within chains, we first use a case study of a particular product (a specific carbonated soda identified by the barcode) on a particular day (December 1st, 2016). Figure 2 shows the distribution of prices for this product, with different colors identifying each chain's distribution. Prices are bunched in only a few values and, more importantly, conditional on a chain, there are only a few prices (much fewer prices than the number of stores).[15]

Figure 2: Uniform Pricing of a Carbonated Soda



Notes: Each color refers to a different chain. Data for a particular product (EAN barcode) and date (December 1, 2016).

More formally, Table 2 shows that uniform pricing is a general characteristic of chains in CABA. For

[15] Appendix Figure A2 repeats this exercise for other products.

each day-product-store observation, we define the relative price as the log-price minus the mean log-price across stores for the same day-product. Product prices are almost unique within chains. The average number of unique prices for each good across stores is between 1 and 4.5 for all chains. Given the number of stores per chain, this implies one price per 55 stores on average. Chains have up to 4 types of stores, and part of the price dispersion within chains is explained by price differences between store types. The average number of unique prices by chain-type is always under 3, implying one price per 81 stores. Moreover, price dispersion in CABA is 7% (see Table 1), while price dispersion within chains is smaller, between 0.7% and 4.7%. If we further control for store type within chains, the price dispersion is even smaller.

The last panel of Table 2 refers to the average price of each chain. The relative price of a store is defined as the average relative price across products in the store for a given day. The relative price of the chain is defined as the average across time and stores of these daily relative prices. Chain I is in general the cheapest, with a relative price 3.3% lower than the average. This contrasts significantly with the Chain V relative price, which is 3.2% higher than the average. This ranking, however, hides significant variation across products. For example, the cheapest chain sets 5% of their prices 4.3% above the market average. Similarly, the most expensive chain sets 5% of their prices 10.6% below the market average.

Table 2: Uniform Pricing in Buenos Aires City

	I	**II**	**III**	**IV**	**V**
Price dispersion					
Within chain	2.2	4.3	0.7	4.7	3.5
Unique prices by product	2.95	1.89	1.03	4.52	3.85
Price dispersion by chain-type					
Within chain-type	2.2	1.6	0.7	2.9	1.5
Unique prices by product	2.95	1.11	1.03	1.85	1.84
Prices					
Price rank	1	2	3	4	5
Relative price (%)	-3.3	-3.1	-0.8	2.5	3.2
By product					
Percentile 5	-11.3	-18.4	-9.3	-8.0	-10.6
Percentile 10	-8.8	-12.9	-7.3	-4.4	-7.0
Percentile 25	-5.7	-6.9	-4.0	-0.2	-2.1
Percentile 50	-2.9	-2.4	-1.2	2.8	2.5
Percentile 75	-0.6	1.4	1.5	6.0	8.2
Percentile 90	1.5	6.2	6.0	9.4	14.6
Percentile 95	4.3	9.4	9.5	11.8	19.0

Notes: Price dispersion refers to the average standard deviation of log-standardized prices. This measure is explained in detail in the main text.

Table 3: Uniform Pricing in Argentina

	Mean	Standard deviation	P25	P50	P75
Chain characteristics					
Number of Stores	113.4	181.4	10.5	27.5	116.6
Number of Provinces	5.8	7.1	1.0	2.5	8.0
Types of stores	1.9	1.4	1.0	1.0	2.5
Number of products	1081.1	390.6	892.1	1104.0	1382.3
Price dispersion					
Within chain	2.9	2.8	0.0	2.6	5.3
Unique prices by product	3.9	5.0	1.0	1.2	4.6
Price dispersion by Chain-Type					
Within chain-prov-type	2.2	2.1	0.0	2.3	3.7
Unique prices by product	2.5	2.1	1.0	1.2	4.0
Price dispersion by Chain-Type-Province					
Within chain-prov-type	1.5	1.3	0.0	1.6	2.6
Unique prices by product	1.5	0.7	1.0	1.1	2.0

Notes: Price dispersion refers to the average standard deviation of log-standardized prices. This measure is explained in detail in the main text.

Table 3 expands this analysis to all chains and stores in Argentina, showing that product prices are almost unique within chains not only in CABA but also within chains in Argentina.[16] While the average number of stores per chain in Argentina is over 113, the average number of unique prices by product is only 3.9. Moreover, price dispersion in Argentina is 9.7% (see Table 1), while price dispersion within chains is on average less than one-third of that (2.9%). As in the case of CABA, if we further control for store type within chains, the price dispersion is even smaller. While for most multi-province chains the average number of unique prices is smaller if we compute unique prices by chain-province, Section 4.3shows that the relation between price dispersion and the number of provinces a chain operates in is positive but relatively flat.[17]

[16] Table 3 shows summary statistics while Appendix Table A1 shows the chain level information.

[17] The average number of provinces in which a chain operates is 5.4. The distribution, however, is right skewed, with almost 50% of chains operating in only one province and three chains operating in almost all provinces.

Table 4: Uniform Price Changes

	CABA	**Argentina**
Price changes: Unconditional		
Share with change	2.72%	2.88%
Share increase	1.80%	1.84%
Share decrease	0.92%	1.04%
Std. deviation of price change	11.92%	14.92%
Price changes: Category synchronization		
Changed other products of same category, chain level	11.82%	11.40%
Changed other products of same category, store level	27.53%	29.00%
Price changes: Chain synchronization		
Changed in other stores of any chain	13.04%	5.53%
Std. deviation of price change	2.32%	5.66%
Changed in other stores of same chain	37.27%	29.93%
Std. deviation of price change	1.84%	3.25%
Changed in other stores of same type and chain	60.01%	38.27%
Std. deviation of price change	1.32%	2.85%
Changed in other stores of same province and chain	37.27%	64.96%
Std. deviation of price change	1.84%	1.23%

Notes: Statistics are in daily frequency. For example, 2.72% of prices are changed everyday in CABA. "Price changes by store" refers to the share of prices that were changed by stores that changed the price of at least one product.

Price Changes: Table 4 studies the intensive and extensive margins of price changes in CABA and Argentina, highlighting the large synchronization in price changes across stores of the same chain. Around 2.8% of prices are changed every day, with approximately two-third price increases and one-third price decreases. Midrigan (2011) highlights that price changes tend to occur at similar times for products of the same category in the US. This is also true in our data. Among products that change prices in CABA, only 13% of other stores in any chain change prices. For products that change prices, we observe that around 27% of other products in the same level-three 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 30–37% of other stores in the same chain change the price of the same product on the same day. The standard deviation of these price changes is approximately one-sixth of the unconditional standard deviation of price changes. Moreover, if we focus only on stores of the same type (for CABA) or in same province (for Argentina) within the same chain, the share of stores that change prices increases to over 60%, with an even smaller dispersion of changes. This evidence suggests that chains coordinate their price changes across stores.[18]

[18]Appendix Table A2 shows that price-change coordination at the chain level also holds when looking at weekly or biweekly data.

Variance Decomposition: In Appendix B we introduce a statistical model to perform a variance decomposition of prices and formally highlight the role of chains in pricing. The basic statistical model proposes that the log-price $p_{g,s,c}$, of 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 $\epsilon_{g,s,c}$ comes from different stores of the same chain setting different prices for the same product:

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

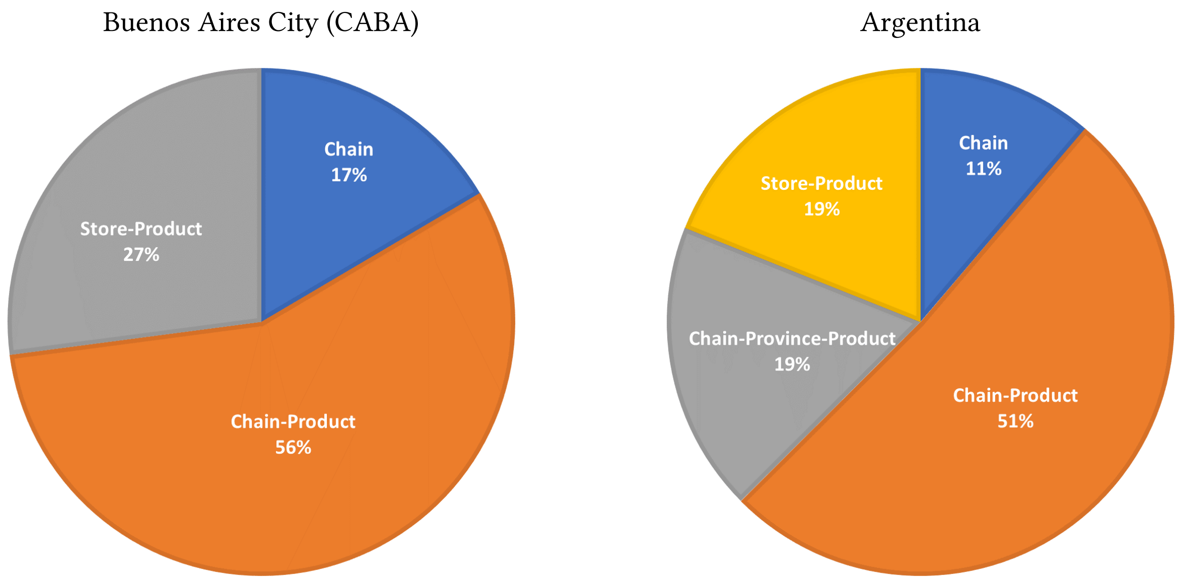
Under some assumptions specified in Appendix B that allow us to simplify the estimation (which is important given the size of our sample), we can decompose relative price variation in a chain component, a chain-product component, and the residual:

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

Figure 3 shows that in CABA, 17% of the price variation is driven by some chains being generally more expensive than others. Once we control for average prices of products by chain, 73% (17% + 56%) of the price dispersion is explained. Using all the data from Argentina, we find that average chain prices per product explain 62% (11% + 51%) of price variation. A simple extension to the statistical model allows us to study the role of province variation. Controlling for price differences across provinces by chain explains another 19%. In other words, consistent with Table 2 and A1, price variation across stores within chains is small, driving only 27% and 19% of the total relative price dispersion for CABA and Argentina, respectively.[19]

[19] Appendix B shows additional results and verifies that the results are robust to alternative specifications. We highlight also that the results are very similar if we do the variance decomposition for Argentina, keeping only chains that are in more than one province.

Figure 3: Variance Decomposition of Prices



Notes: We perform a variance decomposition of prices to formally highlight the role of chains relative to stores in pricing. See details in Appendix B.

4.2 Correlation with products characteristics

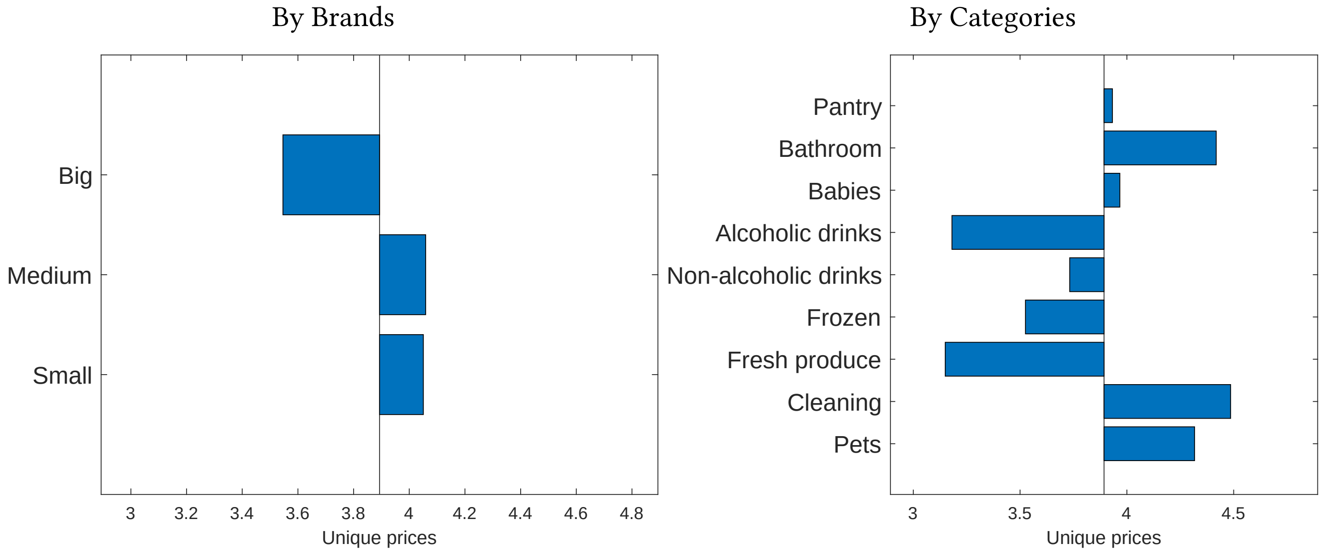
Uniform pricing is similar across products with different characteristics. First, we use the barcodes to identify the brand of the product and split brands in three size groups according to the number of products available.[20] Chains set about 3.9 unique prices per product across stores. The left panel of Figure 4 shows that products from big brands have about 3.6 unique prices by chain, while products from medium and small brands have about 4 unique prices. Hence, there is very little variation across brand sizes.

We also find small variation across product categories (as defined by our data source Precios Claros). The right panel of Figure 4 shows the number of unique prices across nine categories. The range goes from about 3.2 unique prices for alcoholic drinks and fresh produce to about 4.5 unique prices for bathroom or cleaning categories.

Overall, while there is some variation across brands and categories, we find that uniform prices is a general property of grocery prices and is not explained by observable product characteristics.

[20]We use the first six digits of the EAN code (similar to the UPC code in the US), to do a first identification of the brand in the data. Given that these six digits may mix brands with various manufacturers codes, we manually clean the results. We have 154 brands and, on average, each brand has about 11 products. We measure the size of the brand according to the number of products in our sample, and divide the products into three groups (of equal number of products) according to their brand's size. On average, there are about 5, 34, and 113 products per brand in the "small," "medium," and "large" groups, respectively.

Figure 4: Uniform Pricing: Brands and Categories



Notes: The left panel shows the number of unique prices according to the brand of the products. We measure the size of the brand according to the number of products in our sample, and divide the proucts into three groups (of equal number of products) according to their brand's size. On average, there are about 5, 34, and 113 products per brand in the "small," "medium," and "large" groups, respectively. The right panel shows the number of unique prices according by products' category.

4.3 Correlation with Chain Characteristics

We merge information on the location of stores with 2010 Census data to describe the characteristics of each chain's locations. We use the most precise definition of a location in the Census data (i.e., *departamento*s, *partidos* or *comunas,* depending on the region), with a total of 528 locations. These locations are generally large, on average 7,300km^2 in size with a population of 79,000 people. The median location in which stores are located, however, is smaller in size and more densely populated (186 km^2 with 190,000 people).[21] More importantly, we are able to obtain information on the education, employment, and home characteristics of the people living in those areas.

Table 5 performs a simple OLS regression of uniform pricing (measured using the standard deviation of relative prices within each chain) on different chain characteristics. The standard deviation of relative prices increases with the number of stores, but this becomes insignificant once we control for the number of provinces in which a chain operates. The number of types of stores is also correlated with the amount of price dispersion, diminishing the explanatory power of the number of provinces. One potential hypothesis is that chains with greater variance in store-location characteristics will have higher incentives to set different prices. We find that the standard deviation of relative prices does increase with variance in store-location characteristics (either education or distance to competition) but, once

[21]Means are approximately 3,500km^2 and 310,000 individuals.

again, becomes insignificant once we control for the number of types of stores and number of provinces in which a chain operates.

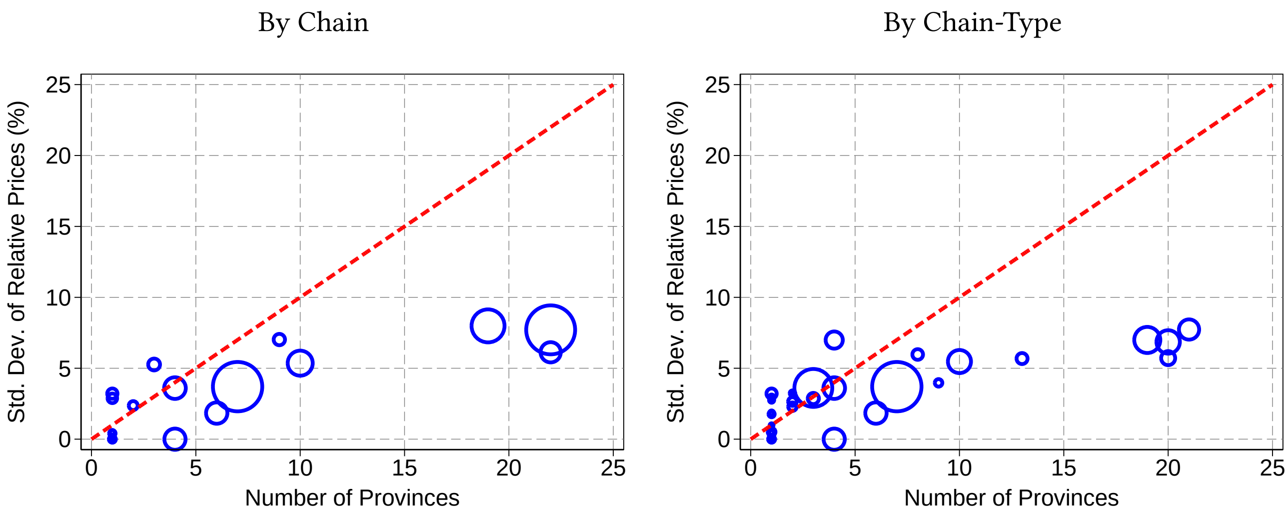
Table 5: Uniform Pricing and Chain Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
Log(number of stores)	1.208***	-0.0206	0.215			0.400
	(0.282)	(0.425)	(0.359)			(0.486)
Log(number of provinces)		2.049***	1.232**			1.408**
		(0.602)	(0.567)			(0.640)
Log(number of types of stores)			1.824***			1.636**
			(0.609)			(0.702)
Var(Log(education) within chain)				131.0**		-42.05
				(49.11)		(55.93)
Var(Log(distance) within chain)					1.588***	-0.0503
					(0.530)	(0.477)
Observations	20	20	20	20	20	20
R-squared	0.505	0.706	0.811	0.283	0.333	0.819

*Notes: Uniform pricing is measured using the standard deviation of relative prices within each chain. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

The left panel of Figure 5 plots the relation between uniform pricing and the number of provinces in which a chain operates. The relation is positive but relatively flat. The number of stores, shown by the size of each circle, does not seem to affect the standard deviation of relative prices. The right panel of Figure 5 plots the same relation but defines chains in a stricter way, i.e., according to chain-types. In this case, the relation between uniform pricing and the number of provinces is even weaker, suggesting that chains may use subdivisions within the chain to partially discriminate prices. Once that is done, price differentiation between locations is not as strong.

Figure 5: Uniform Pricing and Number of Provinces



Notes: Each circle refers to a chain or a chain-type. The size of the circle increases with the number of stores in the chain or chain-type.

Table 6: Relative Dispersion of Chain Location Characteristics

	Average	Std. Dev.
Years of education	0.33	0.39
Home characteristics	0.41	0.40
Number of children	0.30	0.40
House ownership	0.40	0.46
Age	0.44	0.46

Notes: We compute the variance of the log of alternative characteristics for locations in which a chain operates relative to the unconditional variance. This table reports the average and standard deviations of these measures across chains.

Store locations are not exogenous, so we might expect that chains tend to operate stores in locations with similar characteristics (e.g., for reputation or customer demand reasons). To study this hypothesis, we compute the variance of the log of alternative characteristics for locations in which a chain operates relative to the unconditional variance. Table 6 shows that the averages across chains for alternative characteristics (e.g., education, number of children, or age of the head of household) are always under one-half, confirming that chains locate their stores in relatively similar places.

4.4 Effects of Regional Shocks

We have reported consistent evidence that firms' pricing decisions almost do not vary with store characteristics; that is, most chains tend to have a single price per product across their stores. One potential implication of this fact is that grocery store pricing will not change with local conditions or shocks. In this section we introduce evidence on monthly employment levels for each province to evaluate whether average store prices fluctuate with local labor market conditions.[22]

Given the evidence presented on uniform pricing, we expect that prices in stores of chains that operate in many regions will not react to local labor market conditions, while stores of chains operating almost exclusively in one region will react to local conditions. For each store s we define three measures. First, for prices, let $\Delta p_{s,t}$ be the annual change in the average relative price in store s and month t. Second, we measure the relative importance of a province for a chain by the local share. Let $c(s)$ refer to the chain of store s and $prov(s)$ the province of store s. We define the chain's local share $local_{s,t}$ as the share of stores of chain $c(s)$ that belong to province $prov(s)$ in month t. More formally,

$$local_{s,t} = \frac{N_{c(s),t}^{prov(s)}}{N_{c(s),t}},$$

where $N_{c(s)}^{prov(s)}$ is the number of stores of chain $c(s)$ in province $prov(s)$ and month t, while $N_{c(s),t}$ is the total number of stores of chain $c(s)$ in month t. Third, for local conditions, let $\Delta e_{prov(s),t}$ be the annual change in log employment in the province $prov(s)$ of store s in month t. Table 7 evaluates how $\Delta p_{s,t}$ relates to $\Delta e_{prov(s),t}$ and, more importantly, how that relation depends on the local share $local_{s,t}$.

The first column of Table 7 shows that average-price growth per store is not significantly related to employment growth. In all our analysis, we control for store fixed effects in order to control for trends in either store or local characteristics. Once we split the sample by local share, however, columns (2) and (3) show that the relation is significantly positive for stores with a local share above the median (i.e., above one-third approximately) but not for those below.

Next, we do a more formal analysis of the role of the local share by including the interaction between $local_{s,t}$ and $\Delta e_{prov(s),t}$. We estimate

$$\Delta p_{s,t} = \alpha_s + \gamma_t + \delta\ local_{s,t} + \rho\ \Delta e_{prov(s),t} + \beta\ local_{s,t}\ \times\ \Delta e_{prov(s),t} + \epsilon_{s,t}. \tag{1}$$

The coefficient of interest is the interaction term β. Columns (4) and (5) show that the interaction term is significant and positive, even after controlling for time fixed effects. Figure 6 plots the marginal effect of employment growth $\Delta e_{prov(s),t}$ on store price growth $\Delta p_{s,t}$ for stores with different levels of local shares $local_{s,t}$, showing that prices in stores with larger local shares covary more with local conditions. This means that a 1 percent change in employment growth ($\Delta e_{prov(s),t}$) implies a 0.5 percent change in

[22] We would like to have more precise definitions of labor market conditions, but we are limited by data availability.

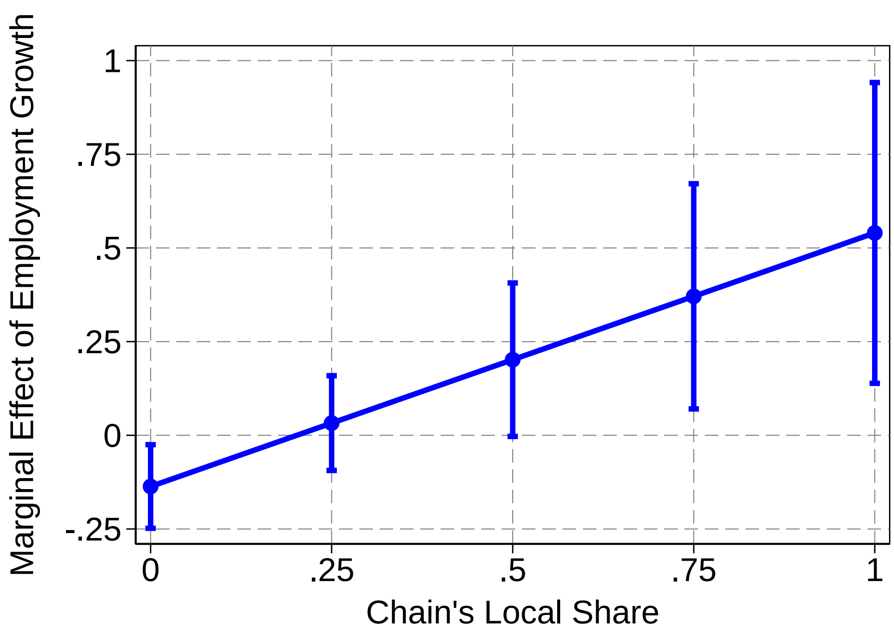
prices ($\Delta p_{s,t}$) for chains with a local share of 100%, but almost no change for chains with a local share below 25%.

Table 7: Regional Shocks and Store Prices

	(1) All	(2) Local share < Median	(3) Local share > Median	(4) All	(5) All
Emp. growth $\left(\Delta e_{prov(s),t}\right)$	-0.0197	-0.124**	0.490***	-0.137**	-0.174***
	(0.0625)	(0.0538)	(0.157)	(0.0569)	(0.0582)
Local share ($local_{s,t}$)				-0.269	-0.237
				(0.189)	(0.144)
Emp. growth × Local share				0.677***	0.454**
				(0.216)	(0.199)
Observations	24,626	12,372	12,253	24,626	24,626
R-squared	0.463	0.537	0.425	0.472	0.488
Store FE	YES	YES	YES	YES	YES
Time FE	NO	NO	NO	NO	YES

*Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Figure 6: Marginal Effect of Regional Shocks on Store Prices



Notes: This figure reports the marginal effect of employment growth on price growth for different levels of a chain's local share, as obtained from Column (4) in Table 7. The vertical lines refer to the 95% confidence intervals.

5 Model

We build and estimate a model of heterogeneous regions with uniform pricing to study the economic responses to regional and aggregate shocks. We make two extensions to the framework of Bernard, Jensen, Redding, and Schott (2018). First, firms in the retail sector set uniform prices (i.e., the same price across stores). Second, we introduce endogenous labor supply so the labor market clears in each region.

The representative agent in each region has a nested structure of demand as in Hottman, Redding, and Weinstein (2016). There are three final consumption sectors. Sector one corresponds to groceries and is the main focus of our analysis. We map firms in sector 1 to chains in our data. Sector two aggregates all other nationally produced goods, and sector three are imported goods. In sector one and two, firms set prices under monopolistic competition. Sector one has a finite number of firms (mapped directly to our grocery store data), which set the same price across regions (i.e, prices are uniform). Sector two, for simplicity, has a continuum of producers and flexible prices (i.e., different prices across regions). In sector three, international prices are taken as given.

In each region $r = 1, \ldots, R$ there is a representative agent. Regions have three sources of heterogeneity. First, there is variation in size N_r (mapped to population size), which allows us to study heterogeneous effects between small and large regions. Second, households have different preferences across sellers, generating the variation on the market shares across regions that we see in the data. Finally, exports are region-specific and the source of exogenous regional and aggregate shocks.

In this model there are price changes due to variations in the marginal costs but our main conclusion is robust to alternative assumptions. In Appendix C we present a simple model in which price changes are driven by demand shocks, instead of marginal costs, through changes in the demand elasticity (due to non-homothetic preferences and income shocks). We find the same qualitative results as in our baseline model: (i) firms setting uniform prices weigh each region according to their relative sizes, (ii) regional price elasticities are smaller than aggregate ones, (iii) regional elasticities are more biased measures of aggregate ones when regions are smaller or firms' sales are more equally distributed across regions.

5.1 Households

There is a representative agent in each region r with preferences

$$U_r = c_r - \Psi \frac{\ell^{1+\phi}}{1+\phi},$$

where c_r is the final consumption and ℓ_r is the labor supply. The budget constraint is

$$P_r c_r = w_r \ell_r + \pi_r \equiv y_r,$$

where P_r and w_r are the aggregate price index and wages in region r, respectively. The household is the owner of regional profits π_r. The optimal labor supply is

$$\ell_r = \left(\frac{1}{\Psi}\frac{w_r}{P_r}\right)^{\frac{1}{\phi}}.$$

Aggregate labor supply is $L_r^s = N_r \ell_r$ where N_r is the size of region r.

Demand across sectors Final consumption c_r combines goods from three sectors. Aggregate consumption is Cobb-Douglas

$$\ln(c_r) = \sum_{n=1}^{3} \lambda^n \ln(c_r^n),$$

with sector n weight λ^n such that $\sum_{n=1}^{3} \lambda^n = 1$. Sector one corresponds to groceries, sector two captures the rest of nationally produced goods, and sector three are the imported goods. The budget constraint is

$$\sum_{n=1}^{3} P_r^n c_r^n = y_r,$$

where P_r^n and c_r^n are the price index and consumption aggregator of sector n. We normalize the price of imported goods, $P_r^3 = 1$. Households have constant expenditure shares across sectors due to the Cobb-Douglas preferences,

$$c_r^n = \lambda^n \frac{y_r}{P_r^n},$$

and the sector's n price index is

$$P_r = \prod_{i=n}^{3} \left(\frac{P_r^n}{\lambda^n}\right)^{\lambda^n}.$$

Demand within sectors Within each sector $n = 1, 2$, there is a continuum of symmetric categories $g \in \Omega^n = [0, 1]$

$$\ln(c_r^n) = \int_{g \in \Omega^n} \ln c_{rg}^n dg,$$

For each category g there are many firms setting prices under monopolistic competition denoted by $\Omega_{rg}^{n,F}$. Sector one has a finite number of firms while sector two, for simplicity, has a continuum of firms. Thus, c_{rg}^n is an aggregator of consumption from sector n, category g, in region r given by

$$c^n_{rg} = \begin{cases} \left[\sum_{f\in\Omega^{n,F}_{rg}} \left(\lambda^{n,F}_{rgf} c^{n,F}_{rgf}\right)^{\frac{\sigma^n-1}{\sigma^n}}\right]^{\frac{\sigma^n}{\sigma^n-1}} & \text{for } n=1 \\ \\ \left[\int_{f\in\Omega^{n,F}_{rg}} \left(\lambda^{n,F}_{rgf} c^{n,F}_{rgf}\right)^{\frac{\sigma^n-1}{\sigma^n}}\right]^{\frac{\sigma^n}{\sigma^n-1}} & \text{for } n=2 \end{cases},$$

where $\sigma^n > 1$ is the elasticity of substitution across goods on sector n, category g, and $\lambda^{n,F}_{rgf} > 0$ is a firm f taste parameter. Here, $c^{n,F}_{rgf}$ is the consumption of goods from firm f in sector n, category g, region r. Individual consumption demands are

$$c^{n,F}_{rgf} = \left(\frac{1}{P^{n,F}_{rgf}}\right)^{\sigma^n} \left(\lambda^{n,F}_{rgf} P^n_{rg}\right)^{\sigma^n-1} (\lambda^n y_r)$$

and aggregate regional demand is

$$C^{n,F}_{rgf} = N_r c^{n,F}_{rgf}. \tag{2}$$

The sector n, region r, good g price index is

$$P^n_{rg} = \begin{cases} \left(\sum_{f\in\Omega^{n,F}_{rg}} \left(\frac{P^{n,F}_{rgf}}{\lambda^{n,F}_{rgf}}\right)^{1-\sigma^n}\right)^{\frac{1}{1-\sigma^n}} & \text{for } n=1 \\ \\ \left(\int_{f\in\Omega^{n,F}_{rg}} \left(\frac{P^{n,F}_{rgf}}{\lambda^{n,F}_{rgf}}\right)^{1-\sigma^n}\right)^{\frac{1}{1-\sigma^n}} & \text{for } n=2 \end{cases}. \tag{3}$$

where $P^{n,F}_{rgf}$ is the price of goods from firm f in sector n, category g, region r. As all categories g are symmetric, $P^n_r = P^n_{rg}$.

5.2 Price setting for final goods producers

The marginal cost of producing one unit of final good is δ^n_{rgf}. Firms in sector $n = 1$ set the same price in all regions

$$\pi^{n,F}_{gf} = \max_{P^{n,F}_{gf}} \sum_{r\in\Omega^{n,F}_{gf}} C^{n,F}_{rgf} \left(P^{n,F}_{gf} - \delta^n_{rgf}\right)$$

subject to (3) and (2), where $\Omega_{gf}^{n,F}$ is the set of regions in which the firm f is active (i.e., $\lambda_{rgf}^{n,F} > 0$). The optimal price is

$$P_{gf}^{n,F} = \frac{\sum_{r\in\Omega_{gf}^{n,F}} \gamma_{rgf}^{n} \left(\sigma^n - \left(\sigma^n - 1\right) s_{rgf}^{n}\right) \delta_{rgf}^{n}}{\sum_{r\in\Omega_{gf}^{n,F}} \gamma_{rgf}^{n} \left(\sigma^n - \left(\sigma^n - 1\right) s_{rgf}^{n} - 1\right)}$$

where γ_{rgf}^{n} is the share of region r in all sales of firm f and s_{rgf}^{n} is the market share of firm f, from sector n, category g in region r

$$\gamma_{rgf}^{n} = \frac{C_{rgf}^{n,F}}{\sum_{r'\in\Omega_{gf}^{n,F}} C_{r'gf}^{n,F}} \qquad s_{rgf}^{n} = \frac{P_{rgf}^{n,F} C_{rgf}^{n,F}}{\sum_{f'} P_{rgf'}^{n,F} C_{rgf'}^{n,F}}.$$

The optimal price has three main forces. First, consider a firm that is in only one region (so $\gamma_{r'gf}^{n} = 1$ for only region r') and does not have market power (i.e., $s_{r'gf}^{n} = 0$). In this case the price is just the standard markup $\frac{\sigma^n}{\sigma^n - 1}$ over marginal cost δ_{rgf}^{n}. Second, consider a firm that is also in one region but has some market power. For that firm, as in Atkeson and Burstein (2008), the optimal price involves markup $\frac{\sigma^n - (\sigma^n - 1) s_{rgf}^{n}}{(\sigma^n - 1)\left(1 - s_{rgf}^{n}\right)}$ which depends on the market share. The markup is an increasing function of the firm's market share s_{rgf}^{n}. Finally, a firm that is active in multiple regions sets the price taking into account the demand elasticity in each region as well as the share of sales in each region. A region with a larger shares of total sale will have a larger weight on the pricing decision. This new force appears due to uniform pricing and is a key mechanism that generates spillover across regions.

In sector $n = 2$, there is a continuum of firms setting flexible prices (i.e., one price in each region). Its maximization problem in each region is

$$\pi_{rgf}^{n,F} = \max_{P_{rgf}^{n,F}} C_{rgf}^{n,F} \left(P_{rgf}^{n,F} - \delta_{rgf}^{n}\right)$$

subject to (3) and (2). The optimal price in this case is just a constant markup over marginal cost

$$P_{rgf}^{n,F} = \frac{\sigma^n}{\sigma^n - 1} \delta_{rgf}^{n}.$$

5.3 Production

Firms combine local labor and a continuum of intermediate inputs to produce the final consumption good as in Bernard, Jensen, Redding, and Schott (2018). Intermediate inputs are produced in every region in the spirit of Eaton and Kortum (2002). Given that many goods sold by grocery stores (as well as firms in other sectors) are from the same producers, we allow intermediate inputs to be sourced from all regions. This introduces linkages across regions, implying that the marginal cost depends on local wages as well as wages in other regions. Together with uniform prices, this will make elasticities to regional shocks different from elasticities to aggregate ones.

Intermediate Inputs Intermediate inputs producers have a linear technology that uses labor and are under perfect competition. The cost of production for an intermediate good l sourced from region j for each firm f, in sector n, category g, in region r is

$$a^n_{jrfg}(l) = \frac{w_j}{z^n_{jrfg}(l)},$$

where $z^n_{jrfg}(l)$ is a stochastic productivity drawn independently for each buyer from a Frechet distribution

$$G^n_{jrfg}(z) = e^{-T_j^{-\theta}},$$

where T_j is the scale parameter that determines the average productivity from source region j and θ is the shape parameter that determines the dispersion of productivity.

Final good firms choose to source intermediate inputs from the cheapest firms (i.e., those with the highest productivity). Thus, the relevant price is the minimum of all prices for each input. Because of the Frechet distribution assumption, the minimum price across all possible sources is also Frechet distributed as

$$G^n_{rfg}(a) = 1 - e^{-\Phi a^\theta}$$
$$\Phi = \sum_j T_j w_j^{-\theta}.$$

We assume that $T_j = \bar{T} N_r$ such that in an economy in which all regions are identical except for the size of their populations, regions also have the same equilibrium wages and sector shares.

Final Goods Final goods production combines intermediate inputs $Y(l)$ and local labor L, with production function

$$Q^n_{rfg} = \left(\frac{L^n_{rfg}}{\alpha_n}\right)^{\alpha_n} \left(\frac{\int_0^1 Y^n_{rfg}(l)^{\frac{\eta-1}{\eta}}\, dl}{(1-\alpha_n)^{\frac{\eta-1}{\eta}}}\right)^{\frac{(1-\alpha_n)\eta}{\eta-1}},$$

where α_g is the labor share and η is the elasticity of substitution across intermediate inputs. The labor demand is

$$L^n_{rfg} = \alpha_n \frac{\delta^n_{rgf}}{w_r} Q^n_{rfg}$$

where the marginal cost δ^n_{rgf} is

$$\delta^n_{rgf} = w_r^{\alpha_n} \gamma^{1-\alpha_n} (\Phi)^{-\frac{1-\alpha_n}{\theta}}.$$

where $\gamma = \left(\Gamma\left(\frac{\theta+1-\eta}{\theta}\right)\right)^{\frac{1}{1-\eta}}$.

The probability that firm f (of sector n, category g) in region r buys inputs from region j is

$$\mu^n_{jrfg} = \frac{T_j w_j^{-\theta}}{\sum_{j'} T_{j'} w_{j'}^{-\theta}}.$$

Note that μ^n_{jmfg} also corresponds to the share of expenditure on inputs from that source country in its total expenditure on variable inputs.[23]

Hence, the labor demand from intermediate producers is

$$L^{n,int}_{jrfg} = \mu^n_{jrfg} \frac{\left(1-\alpha_g\right)\delta^n_{rgf}}{w_j} Q^n_{rfg}$$

and the total labor demand from the intermediate production sector is

$$L^{1,int}_r = \int_{g\in\Omega^n} \left(\sum_{r=1}^{R} \sum_{f\in\Omega^{n,F}_{rg}} L_{jrfg} \right) dg$$

$$L^{2,int}_r = \int_{g\in\Omega^n} \left(\sum_{r=1}^{R} \int_{f\in\Omega^{n,F}_{rg}} L_{jrfg} \right) dg.$$

Exported Good In each region there is production of a tradable good with technology $z_r \left(L^x_r\right)^{\alpha^x}$. This sector takes the international price P^*_r as given, which is the source of regional shocks. The representative firm in this sector solves

$$\pi^x_r = \max_{L^x_r} P^*_r z_r \left(L^x_r\right)^{\alpha^x_r} - w_r L^x_r,$$

with labor demand

$$L^x_r = \left(\frac{P^*_r z_r \alpha^x_r}{w_r}\right)^{\frac{1}{1-\alpha^x}}.$$

We assume that $z_r = \bar{z}_r L_r^{1-\alpha^x}$ and set $\bar{z}_r$ such that in steady state there is trade balance at the regional level. The second term, $L_r^{1-\alpha^x}$, ensures that in an economy in which all regions are identical except for the size of their populations, regions also have the same equilibrium wages and sector shares.

[23] This is a standard result (e.g., Eaton and Kortum, 2002). An implication of the Frechet assumption for intermediate inputs productivity is that the average prices of intermediate inputs conditional on sourcing those inputs from a given region are the same across all source regions. Therefore, the probability that a firm f in production region r obtains an input from source region j $\left(\mu^n_{jrfg}\right)$ also corresponds to its share of expenditure on inputs from that source region in its total expenditure on inputs.

5.4 Equilibrium: Labor market and profits

There are five sources of labor demand. For each sector $n = 1, 2$, there is labor demand from final and intermediate goods producers, and the exportable sector also demands labor. Hence, the regional labor market clearing condition is

$$L^1_{rfg} + L^2_{rfg} + L^{1,int}_r + L^{2,int}_r + L^x_r = L_r.$$

Finally, regional profits correspond to the regional profits generated in the three sectors in region r

$$\pi_r = \frac{1}{N_r}\left(\int_{g\in\Omega^1}\left(\sum_{f\in\Omega^{1,F}_{rg}} \pi^{1,F}_{rgf}\right)dg + \int_{g\in\Omega^2}\left(\int_{f\in\Omega^{2,F}_{rg}} \pi^{2,F}_{rgf}\right)dg + \pi^x_r\right).$$

6 Quantitative Exploration

In this section we quantitatively evaluate the implications of uniform versus flexible pricing.

6.1 Calibration

We calibrate the model with uniform pricing in steady state, assuming that model regions represent the 24 Argentinean provinces (the smallest geographic division for which we have employment data), mapping firms in sector 1 to chains in our data. We calibrate most of the parameters externally (i.e., without simulating the model), but for some parameters we use a simulated method of moments. Table 8 shows the parameters together with their sources or estimated moments. Even though all moments matter for all parameters estimated using simulated method of moments, each row highlights the moment that is most informative for each parameter.

Table 8: Estimated Parameters and Moments

Parameter	Value	Description	Moment	Data	Model
External					
ϕ	2	Labor disutility	Frisch elasticity	1/2	1/2
σ^1	4.50	Substitutability between firms ($n = 1$)	Elasticity from Nielsen (Hottman 2019)	4.5	4.5
σ^2	7.66	Substitutability between firms ($n = 2$)	Markup (Boar and Midrigan 2019)	15%	15%
η	7	Substitutability between int. inputs	Elasticity from Nielsen (Hottman 2019)	7	7
α_2	0.66	Labor share of production ($n = 2$)	Labor share of costs	0.66	0.66
α_x	0.66	Labor share of production (exports)	Labor share of revenue	0.66	0.66
λ_i	$\{.3, .6, .1\}$	Consumption expenditure shares	CPI consumption basket shares		
N_r	See Figure 7	Region's available labor	Provincial population shares of country (Census)		
$\lambda_{rgf}^{n,F}$	See Figure 7	Preferences for chains	Store distributions by province		
Internal					
Ψ	3.54	Labor disutility	Share of time working	0.35	0.35
α_1	.91	Local labor share of production ($n = 1$)	Reg: Local share/employment effect	0.68	0.67
θ	14.8	Int. inputs: Frechet shape	Own-wage elasticity (Lichter et al 2015)	-0.55	-0.60

Notes: The data of price responses and local shares is based on the estimtes of Section 4.4.

We set $\alpha_x = \alpha_2 = 0.66$ so that the labor share of costs in the exporting sector and labor share of revenue in the final goods sector are equal to 0.66. We set consumption expenditure shares λ_i to match the consumption basket shares in the Argentinean Consumer Price Index. This implies that the grocery store sector involves 30% of expenses while imported goods take approximately 10% of expenditures. The remainder 60% refers to nationally produced goods that do not belong to the grocery store sector.[24] We set $\phi = 2$ to match a Frisch elasticity of one-half.[25]

For the substitutability across firms, σ^n, we do not have information on quantities or markups for Argentina so we use estimates from the US. In Section 6.2.1, however, we show that our main results are robust to variations in these (and other) parameters. Hottman (2019) estimates the elasticity of substitution across firms in the grocery retail sector, implying a value of $\sigma^1 = 4.5$.[26] For other sectors ($n = 2$), we target a markup of 15%, i.e., the average markup in the US as summarized by Boar and Midrigan (2019). This implies $\sigma^2 = 7.66$. We also use the intermediate inputs substitutability estimated by Hottman (2019), i.e., $\eta = 7$.

[24] The CPI index specifies that groceries (food and drinks) amount to 30% of expenditures. Assigning the remaining part to either non-trabable or imported goods is not as clear. We assume that expenses in housing, health, transport, communication, entertainment, education, restaurants and hotels are nationally produced goods (i.e., sector 2 in our model). This leaves the clothing sector (of about 10% of expenditures) that we assume refers to imported goods (i.e., sector 3). Even though imports in Argentina amount to approximately 16% of GDP, many of those imports are not part of final consumption so we believe our assumption of 10% of final goods being imported is reasonable. Nevertheless, in Section 6.2.1 we evaluate the sensitivity of our results to alternative estimations.

[25] See Meghir and Phillips (2010) for a discussion on estimates of the Frisch elasticity.

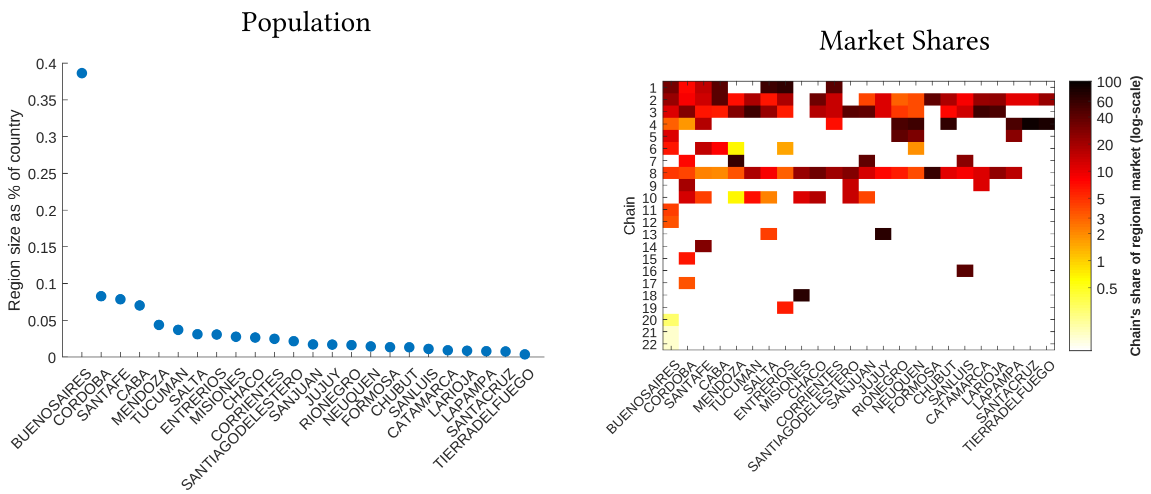
[26] The estimated model implies an average markup in sector 1 of 40.1%. Even though we do not have information on markups in the grocery retail sector in Argentina, we find that this markup is comparable to estimates from the US retail sector—Faig and Jerez (2005) estimate an average markup of 39%—and UK supermarkets—Thomassen, Smith, Seiler, and Schiraldi (2017) find an average markup of 45%.

We measure the relative size of each province N_r using the population by province. We map the firms in sector 1 to the chains in our data. We use store locations in our data to estimate chains' market share in each province. Under the assumption that each store obtains the same revenue, we estimate the market share of each chain as

$$s^n_{rgf} = \frac{\text{Chain's \# of stores in region } r}{\text{\# of stores in region } r}.$$

This share is directly mapped into the region-specific preference $\lambda^{n,F}_{rf}$.[27] Figure 7 shows the population of each province as well as the estimated market share of each chain in each province.

Figure 7: Population sizes and market shares



Notes: The first figure shows the population of each province as a share of the Argentina's total. The second figure shows the market shares of each firm/chain across provinces.

We are left with three parameters (Ψ, α_1 and θ) that we estimate by simulated method of moments. First, to estimate the disutility from working parameter Ψ, we target hours worked to be one-third. Second, Section 4.4 shows that prices of firms with a lower local share react less to regional shocks.[28] We shock the model with an exogenous increase in the price of each regional exported good, one by one—i.e., we increase P^*_r by 4.43%, which corresponds to one standard deviation of export commodities prices in the data. This increases the labor demand for exports in the shocked region, leading to an increase in regional employment, wages and income. We then pool the changes in log-employment and relative prices after each regional shock and estimate a regression equivalent to the one done in the

[27] In order to match the market shares observed in the data s^n_{rgf}, region-specific preferences can be backed out as

$$\lambda^{n,F}_{rf} = \left(s^n_{rgf}\right)^{\frac{1}{\sigma^n - 1}} P^{n,F}_{rgf}\left(\left\{s^n_{rgf}, w_r\right\}\right),$$

where $P^{n,F}_{rgf}\left(\left\{s^n_{rgf}, w_r\right\}\right)$ is the optimal price choice for each firm given the wages and market shares (and other parameters).

[28] In the model, we define the local share as γ^n_{rgf}. In the data, we restrict the set of products such that we compare the price of similar goods across stores. Similarly, in the model, we interpret each variety g as a similar basket sold by different firms f.

data (see equation 1). The coefficient from the effect on relative prices of the interaction between local shares and employment (β in equation 1) is informative about the local labor share of production α_1. The higher α_1, the more marginal costs depend on local labor (and less on nationally-produced intermediate inputs), leading to larger differences between local and multi-regional producers in their price reaction. This leads to a coefficient of $\alpha_1 = 0.91$. Given that our model only has labor inputs, this coefficient may be interpreted more broadly as the share of marginal costs linked to local conditions.

Finally, θ relates to how much labor demand for the production of intermediate inputs changes with relative wages across the country. Thus, an informative moment is how much non-export labor demand changes with wages after the regional shocks mentioned above take place. We estimate this using the own-wage elasticity moment (i.e., the ratio of the percent change in non-export labor to the percent change in wages), which in the data has an average value of -0.55 (Lichter, Peichl, and Siegloch, 2015). As seen in Table 8, the model does a good job at matching the three target moments.

6.2 Regional vs. Aggregate Elasticities

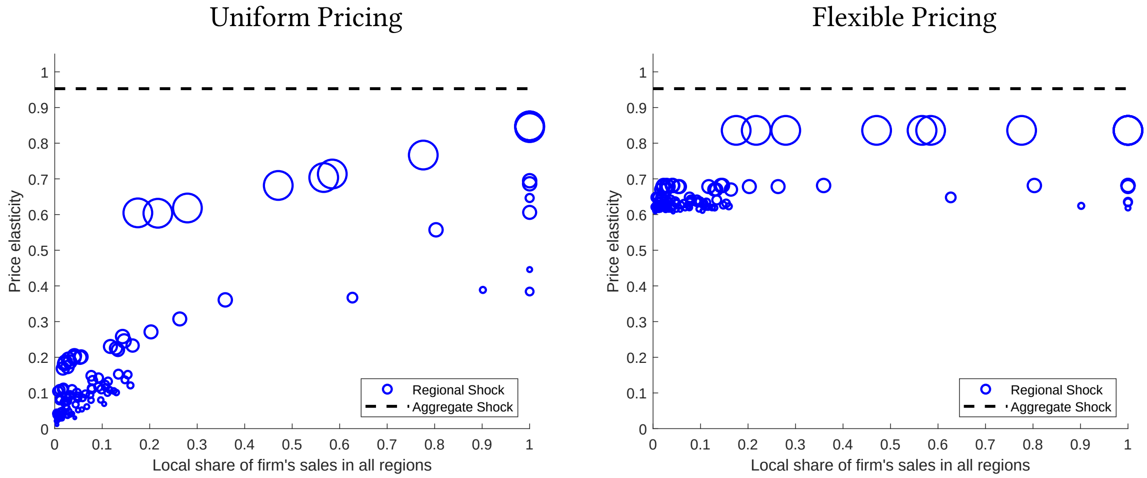
We study the responses of prices to aggregate versus regional shocks. A regional shock, as in the calibration, refers to an increase in the price of the exportable good P_r^* for a single region r. An aggregate shock, instead, refers to an increase in P_r^* for all regions r.[29] These shocks increase labor demand for exports, leading to increased employment, wages and income. We then calculate the elasticity of prices (for each firm) to the regional income: $\varepsilon_{P_{gf}^{n,F},Y_r} = \frac{\Delta \log\left(P_{gf}^{n,F}\right)}{\Delta \log(Y_r)}$.

Uniform vs. Flexible Pricing: We solve a counterfactual model in which firms in sector $n = 1$ can set flexible prices. Figure 8 shows the elasticity $\varepsilon_{P_{gf}^{n,F},Y_r}$ in sector $n = 1$ as a function of the firm's local share, and compare the cases of uniform versus flexible pricing. With uniform prices, firms have to set the same prices across regions. Hence, when the local share is relatively small, the total marginal cost and total demand for that product does not change much. As a result, prices have a small reaction to shocks. On the other hand, when the local share is high, prices react more to regional shocks. In the economy with flexible pricing, the response of prices is similar for all firms regardless of the local share. Thus, the patterns of price reactions in the uniform-pricing economy resemble the empirical findings of Figure 6, while those in the flexible-pricing model do not.[30]

[29] As in the estimation, we increase P_r^* by 4.43%, which corresponds to one standard deviation of export commodities prices in the data. In Section 6.2.1, we show that our main result is almost unchanged if we change the size of the shock.

[30] We model uniform pricing as an exogenous constraint to the firm for tractability. We can quantify how costly this constraint is by evaluating how high does a fixed cost of setting uniform prices need to be for firms not to be willing to deviate and do flexible pricing. We find that the average gain from deviation corresponds to approximately 1.9% of profits.

Figure 8: Regional versus Aggregate Shocks



Notes: We shock the economy with an exogenous increase in price of exports for each region one by one; we increase P_r^* by 4.43%, which corresponds to 1 standard deviation in the data. The first figure shows the response of prices to regional and aggregate shocks, under uniform pricing. The second figure shows the case of flexible pricing. The size of the circles is determined by the size of the regions (i.e., population size).

Regional vs. Aggregate Shocks: The dotted line in Figure 8 shows $\varepsilon_{p_{gf}^{n,F},Y_r}$ when the shocks are aggregate (i.e., the same shock takes place in all regions). In this case, the effect on firms' prices is independent of the local share. Since all regions receive the same export price shock, marginal costs and income increase in all regions, leading to price increases that are independent of local shares. It is also clear that aggregate shocks lead to larger price changes, particularly when the regional shocks take place in regions in which firms have small local shares. For example, firms with local shares around 0.1 display a price elasticity of approximately 0.1–0.2 when the shock is regional, but an elasticity of 0.95 when the shock is aggregate. For firms that are only in one region (i.e., local share of 1), the price elasticity is between 0.4 and 0.85 when the shock is regional, but is 0.95 when the shock is aggregate.

Price elasticities are heterogeneous because of market structure as well as regions' sizes (in addition to local shares). Regions' sizes, as shown by the size of the circles in Figure 8, are particularly important due to the role of intermediate inputs. Since intermediate inputs are produced nationally, the cost in each region depends on wages in all regions. Bigger regions tend to produce more of the intermediate inputs. Hence, when wages increase in a big region, marginal costs of intermediate inputs increase more, which then generates larger price elasticities.

To summarize these results, we study the responses of the price index P_r and total consumption C_r to shocks. We define the elasticities as

$$\varepsilon_{P_r,Y_r} = \frac{\Delta \log (P_r)}{\Delta \log (Y_r)} \qquad \varepsilon_{C_r,Y_r} = \frac{\Delta \log (C_r)}{\Delta \log (Y_r)}$$

and note that $\varepsilon_{P_r,Y_r} + \varepsilon_{C_r,Y_r} = 1$. Table 9 reports the average across regions for these elasticities under different scenarios. Under the baseline economy of uniform pricing with endogenous intermediate inputs, the price elasticity ε_{P_r,Y_r} is 0.56 when the shock is regional but it is 0.86 when the shock is aggregate. The elasticity ratio of regional to aggregate shocks, our main measure of elasticity differences, is $\frac{0.56}{0.86} = 0.66$. In other words, the estimated model predicts an almost one-third smaller price elasticity to a regional shock than to an aggregate one. The intuition is that under uniform pricing prices are set according to the weighted marginal cost of the total economy. If there is a regional shock, the marginal cost will not change much, and, as a result, prices will be sticky to regional shocks. Consumption, therefore, will react more in the region of the shock than under an aggregate shock in which prices do adjust more. Table 9 also reports the consumption elasticity. To compensate for the differences in the price elasticity, the consumption elasticity is 0.43 when the shock is regional, but it is 0.14 when the shock is aggregate.[31]

As mentioned above, the differences between aggregate and regional elasticities is due to uniform pricing as well as intermediate inputs being produced nationally. The bottom panel of Table 9 shows that when these two elements are shut down (i.e., prices are flexible and the cost of as well as labor demand for intermediate inputs is fixed to their baseline values), aggregate and regional shocks lead to the same elasticities. To evaluate the importance of uniform pricing relative to intermediate inputs, we evaluate a third scenario. The middle panel of Table 9 shows that with uniform pricing but fixed intermediate inputs, the price elasticity ratio is 0.83. Given the baseline value of 0.66, this suggests that uniform pricing generates about half of the difference (i.e., $0.83 - 0.66 = 0.17$ of a total of $1 - 0.66 = 0.34$) between regional and aggregate price elasticities. Thus, uniform pricing implies that using regional heterogeneity to infer aggregate price elasticities may lead to a downward bias.

[31] An alternative way to estimate the price elasticity is to regress $\Delta \log(P_r)$ on $\Delta \log(Y_r)$, using data from all regions. This methodology is closer to the geographic economics literature (e.g., Mian and Sufi, 2011; Autor, Dorn, and Hanson, 2013). Using this methodology and regional shocks, we estimate an average price elasticity of between 0.4 and 0.7 (close the true average elasticity in our model of 0.56), depending on whether we include shock source fixed effects (similar to time fixed effects in empirical regressions) or not. However, this methodology is not useful to calculate aggregate elasticities in our model since aggregate shocks lead to the same $\Delta \log(P_r)$ and $\Delta \log(Y_r)$ in all regions r, so the constant in the regression absorbs all the effects.

Table 9: Regional versus Aggregate Shocks

	Price index	Consumption
Uniform pricing		
Regional shock	0.56	0.43
Aggregate shock	0.86	0.14
Elasticity ratio	0.66	3.10
Uniform Pricing + Fixing intermediate inputs		
Regional shock	0.62	0.37
Aggregate shock	0.75	0.24
Elasticity ratio	0.83	1.53
Flexible Pricing + Fixing intermediate inputs		
Regional shock	0.75	0.24
Aggregate shock	0.75	0.24
Elasticity ratio	1.00	1.00

Notes: The table compares the elasticity of the price index and total consumption to regional and aggregate shocks, in the uniform-pricing economy with endogenous intermediate inputs (baseline), uniform-pricing with fixed intermediate inputs, and flexible-pricing with fixed intermediate inputs. We define the elasticity ratio as elasticity to regional relative to aggregate shocks.

Regional Elasticity Heterogeneity: Figure 8 shows that price elasticities are heterogeneous because of market structure as well as regions' sizes. We now formalize this using the price index elasticity ε_{P_r,Y_r} and total consumption elasticity ε_{C_r,Y_r}. We regress the elasticities on the region's size (N_r) and average local share $\left(\overline{\gamma^n_{rgf}}\right)$

$$\text{Regional Elasticity}_r = \alpha + \beta \text{Size}_r + \gamma \text{Avg-Local-Share}_r + \varepsilon_r.$$

Table 10 shows the results using both price and consumption elasticities. First, the larger a region is, the more prices will follow their demand as well as marginal costs, and the response of regional and aggregate shocks will become more similar. This is in line with Figure 8, which shows that regions with larger sizes (i.e., larger circles) display regional elasticities that are closer to the aggregate ones. Second, the larger the average local share, the larger the price elasticity is (and therefore the closer it is to the aggregate one). When the local share is small, firms are more multi-regional, implying that the region is a small share of most sellers' sales. Hence, the prices will react less to a regional shock, which increases the elasticity ratio.

Table 10: Regional Elasticity Heterogeneity

	Price Elasticity	Consumption Elasticity
Avg. local share	0.1108	-0.1113
	[8.16]	[-8.13]
Market size	0.6972	-0.7014
	[18.91]	[-18.88]
R^2	0.97	0.97
N	24	24

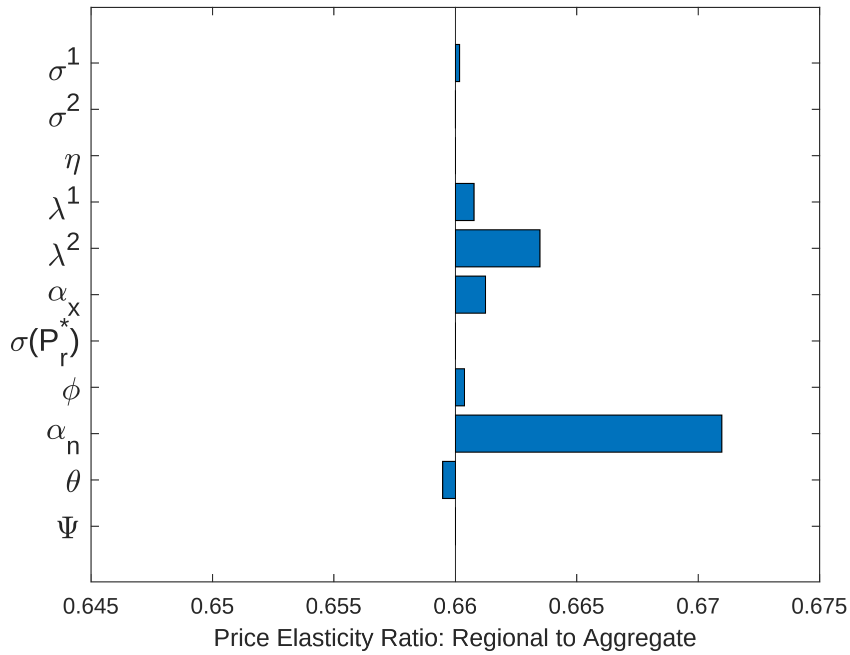
Notes: We shock the economy with an exogenous increase in price of exports for each region one by one; we increase P_r^* by 4.43%, which corresponds to 1 standard deviation in the data. After calculating the elasticity of the price index and total consumption to regional shocks, we regress these on the average local share and market size of each region.

6.2.1 Estimation Sensitivity

The main takeaway of the model is that in an economy with multi-regional sellers, prices react less to regional shocks than to aggregate ones. This implies that using regional heterogeneity to infer aggregate price elasticities may lead to a downward bias due to uniform pricing. In particular, we estimate the regional price elasticity to be on average only two-thirds of the aggregate elasticity. How sensitive is this quantitative result to alternative estimations? Figure 9 shows the model's average elasticity ratio when we increase each parameter by 1%.[32] While we find that most parameters lead to almost no changes, two parameters deserve mentioning. First, the higher the share of expenses on sector 2 (λ_2), the larger the weight of sector 2 in the aggregate price. Since sector 2 has flexible prices, aggregate and regional shocks lead to more similar effects on the price of that sector, and the elasticity ratio increases. Second, the larger α_n, the larger the role of local labor in the production of final goods. As the role of nationally produced intermediate inputs is eliminated (which Table 9 shows that explains about half of the elasticity ratio), the more similar the regional elasticity will be to the aggregate one. Even though a formal analysis would require knowing the standard deviation of the parameters of interest, Figure 9 also shows that the elasticity ratio may be almost unaffected by sizable changes in most parameters.

[32] We follow Andrews, Gentzkow, and Shapiro (2017), as implemented by Elenev, Landvoigt, and Van Nieuwerburgh (2020), and evaluate the elasticity of the moment of interest (i.e., the elasticity ratio) to each parameter in Θ as $\frac{\log(\text{Elasticity Ratio} \mid \Theta e^{\iota\epsilon}) - \log(\text{Elasticity Ratio} \mid \Theta e^{-\iota\epsilon})}{2\epsilon}$, with $\epsilon = 0.01$ and ι a vector selecting the parameter of interest. We then use this to evaluate what the elasticity ratio would be if the parameter was increased by 1%.

Figure 9: Price Elasticity Ratio Sensitivity to 1% Increase of Parameters

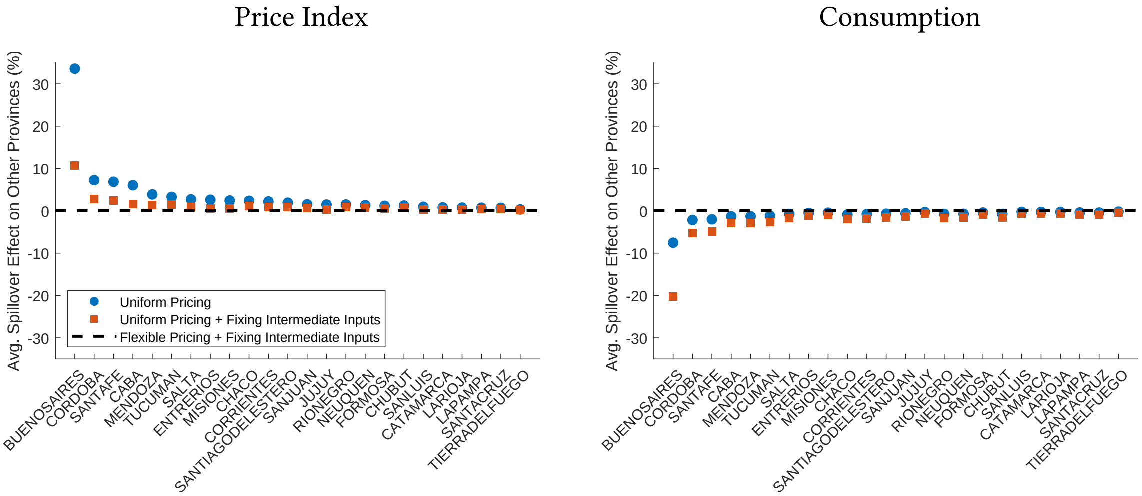


Notes: The figure shows the estimated price elasticity ratio (regional to aggregate) when each parameter is increased by 1% one by one. The vertical line at 0.66 reflects the elasticity ratio in the baseline estimation. When adjusting expenditure shares λ_1 or λ_2, we assume that the share spent on imports (λ_3) adjusts so that expenditure shares sum to one.

6.3 Spillovers from Regional Shocks

Uniform pricing also implies that shocks in one region have spillover effects on other regions. As firms set the same price in all regions due to uniform pricing, a shock in one region will lead to a price change in all regions. To demonstrate this, we separately simulate regional shocks in each region as before but, instead, look at the effect on other regions. Figure 10 shows the average effects of a shock in each region on the price index and total consumption of other regions, all relative to the effects from an aggregate shock.

Figure 10: Regional versus Aggregate Shocks



Notes: We shock the economy with an exogenous increase in price of exports for each region one by one; we increase P_r^* by 4.43%, which corresponds to 1 standard deviation in the data. The first figure shows the average spillover effect on prices of other regions, relative to an aggregate shock. The second figure shows the consumption spillover, also relative to an aggregate shock. Regions are sorted by size.

The average spillover effect on prices is 3.6%, while the one on consumption is -1% (always relative to the effect from an aggregate shock). But results are very heterogeneous depending on where the shock takes place. A shock in Buenos Aires, the largest region, leads to an average increase in prices of approximately 33% (relative to the aggregate shock) in the other regions. This then causes an average decrease in consumption of 7.5% (relative to the consumption increase observed with an aggregate shock). Similar qualitative spillover effects on prices and consumption are observed when the shock takes place in other provinces. However, the magnitudes of the spillover effects are much smaller since the shocks are taking place in much smaller regions. Bigger regions have a larger impact on prices, hence leading to larger spillover effects.

Spillovers occur because of uniform prices as well as intermediate inputs that are nationally produced. The dashed line of Figure 10 shows that when these two elements are shut down (i.e., prices are flexible and the cost of as well as labor demand for intermediate inputs is fixed to their baseline values), there are no spillover effects. To evaluate the importance of uniform pricing relative to intermediate inputs, Figure 10 also shows the spillover effects with uniform pricing but fixed intermediate inputs. While uniform pricing explains all of the negative consumption spillover effects, it only explains about one-third of the total price spillovers: the average price spillover effect is now 1.3% instead of 3.6%.[33]

[33]The existence of intermediate inputs that are nationally produced implies that when one region receives a positive export price shock, its wages increase and a larger share of intermediate inputs is now produced in other regions. This increases the income in other regions, leading to an increase in consumption that partially compensates the decrease generated by the increase in prices.

7 Conclusion

This paper introduces a new database of grocery prices in Argentina, with over 9 million observations per day, to study the importance of chains relative to stores in setting prices. We show that conditional on a product, there is little variation across stores of the same chain; i.e., there is *uniform pricing*. Prices almost do not vary within stores of a chain and prices do not change significantly with regional conditions or shocks, particularly so for chains that operate in many regions.

We study the impact of uniform pricing on estimates of local and aggregate elasticities. We develop a model of heterogeneous regions with uniform pricing. We estimate the model to match the fact that firms operating mostly in one region react more to local shocks. Uniform pricing implies that consumption reacts less in response to an aggregate than to a regional income shock because prices adjust more in response to aggregate shocks. The estimated model predicts an almost one-third lower elasticity of prices to a regional shock than to an aggregate one. This result highlights that some caution may be necessary when using regional shocks to estimate aggregate elasticities, particularly when the relevant prices are set uniformly across regions. Moreover, the recent rise in market-share concentration and of e-commerce (to about 10% and 15% of all retail sales in the US and worldwide, respectively, in 2018) implies that firms are more likely to be active in multiple regions, which reinforces the importance of this channel.

Why would firms set uniform prices instead of customizing prices to local customers? Traditional explanations typically focus on the cost of discriminating, including operation as well as reputation costs. Dobson and Waterson (2008) provide a different reason more closely related to collusion. They show that firms may be better off under uniform pricing even if they have larger market power in some regions. This policy, if applied by all firms under commitment, will soften competition in other markets and may sufficiently raise firm profits overall (at the cost of some local profits). Our paper does not explore this question. Instead, using the model, we take uniform pricing as an exogenous constraint and evaluate its consequences for consumers and firms. We highlight, nevertheless, that the returns to price discrimination for firms in our baseline estimation are low, less than 0.35% of profits on average. Hence, we interpret this to mean that the costs of price discrimination may not need to be as large as one may imagine to justify uniform pricing.

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A Data Appendix

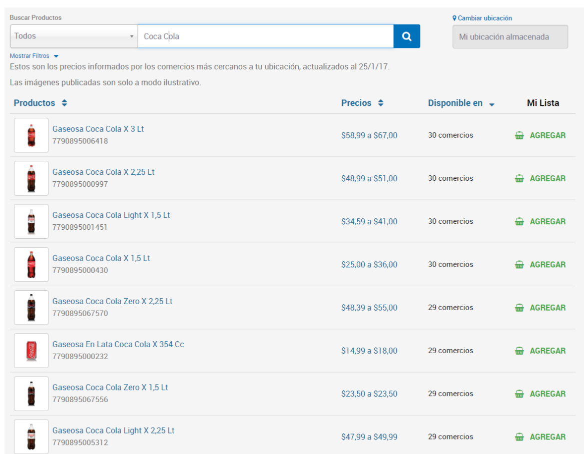
A.1 Website Example

Figure A1 shows an example in which we use the website to search for *Coca-Cola* soda. The second figure shows that after searching for *Coca-Cola*, many varieties of the product are available. The prices in the 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.

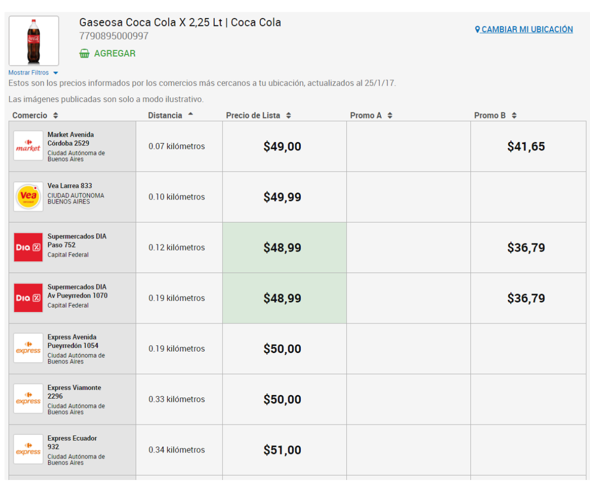
Figure A1: Precios Claros Website

Step 1: Introduce Location

Step 2: Search for Product

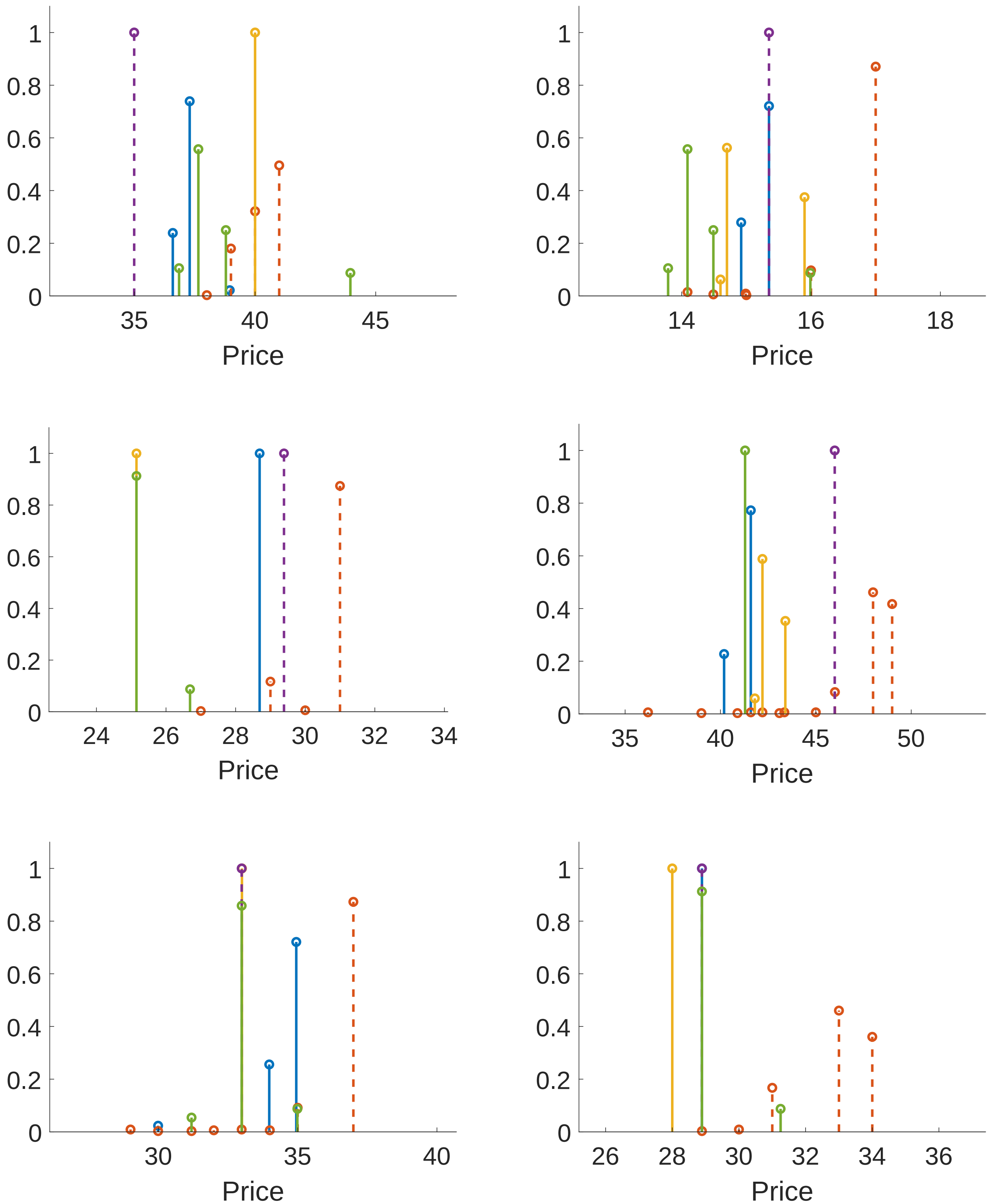


Step 3: Select Product



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

Figure A2: Examples of Uniform Pricing



Source: Precios Claros. Each color refers to a different chain. Data for particular products (barcodes) on a particular day (December 1, 2016).

A.2 Data Validation

The data is self-reported by the chains, but we have several motives to believe that it actually represents the real prices. First, large fines (of up to 3 million US dollars) are applied if stores do not report their prices correctly. Second, micro-price statistics are consistent with the international evidence for countries with annual inflation around 30%. For example, the monthly frequency of price changes is 0.84 and the dispersion of relative prices is 9.7%, both of which are similar to the findings in Alvarez, Beraja, Gonzalez-Rozada, and Neumeyer (2018). Third, we observe a (small) variation in prices for a specific product (barcode) across stores of the same chain and chain type, implying that retailers are not uploading exactly the same price list for all their stores. Fourth, the number of stores by province is consistent with official statistics (see *Encuesta de Supermercados*). Finally, the level of price changes is consistent with official statistics for monthly inflation. This evidence lead us to believe that the self-reported prices are the real ones and there are no mistakes in the database.

A.3 Price Dispersion in All Chains

Table A1 repeats the analysis of Table 2 but for all national chains and shows that uniform pricing is a general characteristic of chains in Argentina.

A.4 Price Change Synchronization

Table A2 shows that price-change coordination at the chain level also holds when looking at weekly or biweekly data.

Table A2: Uniform Price Changes

	Period of analysis		
	1 day	1 week	2 weeks
Changed in other stores of any chain	5.53%	17.65%	27.82%
Std. deviation of price change	5.66%	9.39%	9.46%
Changed in other stores of same chain	29.93%	47.57%	58.89%
Std. deviation of price change	3.25%	4.33%	3.97%
Changed in other stores of same type and chain	38.27%	52.95%	63.13%
Std. deviation of price change	2.85%	3.91%	3.70%
Changed in other stores of same province and chain	64.96%	75.23%	81.25%
Std. deviation of price change	1.23%	1.86%	1.96%

Notes: Statistics are in daily, weekly and biweekly frequency. For example, out of all products that changed prices in one store in a given week, prices also changed in 17.65% other stores of any chain.

Table A1: Uniform Pricing in Argentina

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T
Price dispersion																				
Within chain	0.4	0.5	0.0	0.0	0.0	0.0	2.4	3.7	0.0	6.1	0.0	5.3	2.9	7.0	1.8	3.6	8.0	7.7	3.2	5.4
Unique prices by product	1.01	1.01	1.00	1.00	1.00	1.00	1.11	3.73	1.00	9.08	1.00	3.44	1.13	2.26	2.09	5.40	15.29	18.25	1.37	6.68
Price dispersion by chain-province																				
Within chain-prov	0.4	0.5	0.0	0.0	0.0	0.0	2.3	2.6	0.0	3.8	0.0	5.0	2.9	4.3	1.2	2.8	4.1	5.6	3.2	3.7
Unique prices by product	1.01	1.01	1.00	1.00	1.00	1.00	1.10	2.72	1.00	2.10	1.00	2.74	1.13	1.40	1.10	3.22	3.52	5.36	1.37	2.35
Price dispersion by chain-province-type																				
Within Chain-prov-type	0.4	0.5	0.0	0.0	0.0	0.0	2.0	2.6	0.0	2.5	0.0	2.4	2.5	0.9	1.2	2.8	2.6	3.4	3.2	3.6
Unique prices by product	1.01	1.01	1.00	1.00	1.00	1.00	1.09	2.72	1.00	1.32	1.00	2.17	1.09	1.04	1.10	3.22	1.88	2.30	1.37	2.16
Prices																				
Price rank	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Relative price (%)	-15.7	-10.0	-8.6	-6.8	-6.4	-5.6	-5.1	-3.1	-2.6	-2.3	-2.2	-2.0	-1.5	-0.6	0.1	0.7	1.7	2.2	3.6	4.4
By product																				
Percentile 5	-37.8	-35.0	-30.6	-23.9	-31.8	-28.6	-31.5	-11.6	-14.1	-18.2	-26.8	-29.3	-28.4	-24.7	-8.2	-22.0	-14.8	-13.8	-19.6	-13.0
Percentile 10	-32.4	-27.4	-22.6	-17.9	-25.6	-21.3	-22.2	-8.9	-12.3	-12.7	-21.1	-20.8	-22.2	-17.8	-6.0	-14.1	-9.8	-8.1	-12.0	-7.4
Percentile 25	-23.3	-17.6	-13.0	-11.7	-14.3	-12.6	-12.3	-5.8	-8.6	-5.9	-11.0	-9.2	-11.4	-6.4	-2.9	-3.7	-3.4	-2.1	-2.6	-0.7
Percentile 50	-15.1	-8.5	-7.1	-6.1	-4.4	-5.3	-4.0	-2.7	-3.9	-1.6	-1.8	0.1	-1.5	0.5	-0.2	2.2	1.6	2.9	4.6	5.2
Percentile 75	-7.6	-1.1	-2.0	-0.7	2.0	1.5	3.4	0.0	3.3	2.4	7.5	7.2	9.2	6.9	2.9	7.5	7.2	7.7	11.2	10.5
Percentile 90	-0.6	5.1	2.2	4.2	8.2	8.7	10.9	2.9	7.7	7.0	16.0	13.8	18.0	13.3	6.9	12.5	13.3	11.9	18.0	15.2
Percentile 95	3.2	9.5	5.0	7.6	13.4	13.7	16.1	5.1	12.4	10.2	20.5	17.3	25.0	17.4	9.7	15.8	17.4	14.7	22.4	18.3

Notes: Price dispersion refers to the average standard deviation of log-standardized prices. This measure is explained in detail in the main text.

B Statistical Model of Price Dispersion

We use a statistical model to do a variance decomposition of prices and formally highlight the role of chains behind price setting. 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. We then report average results over time as well as the autocorrelation of the different estimated components.

We propose that the log-price $p_{g,s,c}$ of 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 $\epsilon_{g,s,c}$ comes from different stores of the same chain setting different prices for the same product:

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

In our estimation, we assume that the conditional mean $\mathbb{E}[\beta_c] = 0$, such that α_g absorbs the average price effect. This standardizes prices, facilitating the comparison of prices of different goods that may be more expensive due to their characteristics (e.g., a 2.25 liter bottle of a particular soda vs a 750 milliliter bottle of a shampoo).[34] 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 the 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 stores selling good g, N_c the number of price observations (i.e., good-stores observations) of chain c, and $N_{g,c}$ the number of stores selling good g in chain c.

We then abstract from the price variation due to product characteristics α_g and study dispersion in relative prices. We decompose relative price variation in a chain component, a chain-product component, and the residual:

[34] This is equivalent to analyzing "relative prices," as in Kaplan, Menzio, Rudanko, and Trachter (2019).

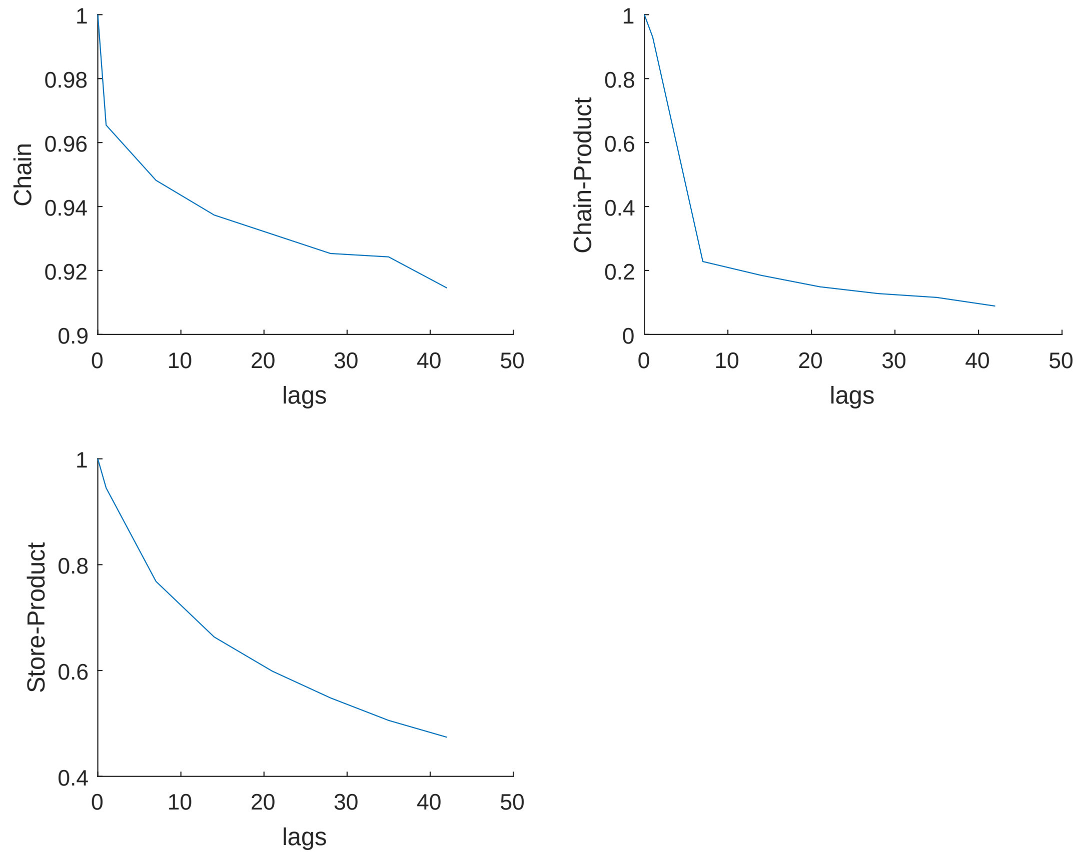
$$\underbrace{\text{Var}\left(p_{g,s,c} - \hat{\alpha}_g\right)}_{\text{Relative Price}} = \underbrace{\text{Var}\left(\hat{\beta}_c\right)}_{\text{Chain}} + \underbrace{\text{Var}\left(\hat{\gamma}_{g,c}\right)}_{\text{Chain-Product}} + \underbrace{\text{Var}\left(\hat{\epsilon}_{g,s,c}\right)}_{\text{Residual}}.$$

Figure 3 in the main text shows that in CABA 17% of price variation is driven by some chains being generally more expensive than others. Once we control for average prices of products by chains, 73% (17% + 56%) of price dispersion is explained. For the Argentinean case, we also estimate the importance of prices in chains at the province-product level. In this case, average chain prices per product explain 62% (11% + 51%) of price variation. Controlling for price differences across provinces by chain explains another 19%. In other words, consistent with Tables 2 and A1, price variation across stores within chains is small, driving only 27% and 19% of the total relative price dispersion for CABA and Argentina, respectively.

Alvarez, Beraja, Gonzalez-Rozada, and Neumeyer (2018) estimate price dispersion in Argentina using a longer time series of price data, from 1988 to 1997, covering a range of monthly inflation between 0 and 200%. They have, however, only 500 products that cannot be precisely compared across stores (since products are defined as narrow categories and don't have barcodes). Our dataset contains a substantially larger number of goods that can be precisely compared across stores since we observe their EAN barcodes. Our estimates for the standard deviation of relative prices is approximately 7% and 10% for CABA and Argentina, respectively. These estimates are near but below the estimates reported by Alvarez, Beraja, Gonzalez-Rozada, and Neumeyer (2018) in periods with inflation levels close to the ones from our time period. One potential explanation for this difference is that we are actually comparing the same products (EAN barcodes) across stores, while they may be comparing different products.

Autocorrelation: Understanding the origin of this price dispersion is important to understanding store price setting as well as consumer choices. Kaplan, Menzio, Rudanko, and Trachter (2019) highlight that a large share of price dispersion comes from 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 more goods at higher prices since it is costly (or not possible) to find lower prices. If chains are the only drivers of price dispersion, the information problem seems more limited, as long as price differences between chains are persistent. Figure B3 shows the autocorrelation of the estimated components $\hat{\beta}_c$, $\hat{\gamma}_{g,c}$, and $\hat{\epsilon}_{g,s,c}$ at different lags of days.

Figure B3: Price Dispersion Persistence



B.1 Alternative Decomposition

Table B3 shows the role of goods categories and store provinces on the variance of relative prices for Argentina. Regarding categories, 51% of the variance is explained by chains setting different relative prices across goods. Variation across categories explain 16% of the variance, while variation within goods of the same category explains the remaining 35%. Moreover, 38% of the variance of relative prices is explained by stores of the same chain setting different prices for the same good. The province of the store explains 19% of that variance, while the other 19% corresponds to different prices in stores of the same province. Finally, Table B4 shows that 19% of the variance of relative prices is explained by stores setting different prices across goods. Chains explain 11% of that variance, and different prices at stores of the same chain explain the additional 8%.

Table B3: Alternative Decomposition: Categories and Provinces

	I	II	III
Chain	11	11	11
Goods			
Chain-good	51		51
Chain-Category		16	
Chain-Category-good		35	
Stores			
Chain-good-store	38	38	
Chain-good-prov			19
Chain-good-prov-store			19
Total	100	100	100

Notes: Roles of goods categories, and stores provinces.

Table B4: Alternative Decomposition: Stores

	IV	V
Chain & Stores		
Store	19	
Chain		11
Chain-store		8
Goods		
Store-good	81	
Chain-store-good		81
Total	100	100

Notes: Roles of stores versus chains.

C Alternative Model

The baseline model in Section 5 has price changes due to variations on marginal costs. Our main conclusions also hold when price change due to demand shocks that changes the demand elasticity (due to non-homothetic preferences and income shocks). We find the same qualitative results as in our baseline model: (i) firms setting uniform prices weigh each region according to their sales share, (ii) regional price elasticities are smaller than aggregate ones, (iii) regional elasticities are more biased measures of aggregate ones when regions are smaller or firms' sales are more equally distributed across regions.

This alternative model has the fewest possible components such that while it is consistent with the data it is also tractable, allowing us to easily identify the key trade-offs across alternative pricing schemes. We extend the standard model of monopolistically competitive firms with a continuum of goods in three key dimensions. First, we add non-homothetic preferences so that prices change with income shocks. We assume preferences similar to Simonovska (2015), as this preference structure allows for analytical tractability. Second, we include multiple regions and variation in market shares across varieties. We assume there are two regions with heterogeneous preferences across varieties to generate variation on market shares. Third, we assume that there is uniform pricing, i.e., the seller has to set the same price in both markets.[35]

Time is discrete and infinite, $t = 0, \ldots, \infty$. There are two cities $j = 1, 2$ with population size M_j and a continuum of differentiated goods $\omega \in [0, 1]$. Each product is sold by a national monopolistic firm that chooses to sell in either one or both cities. Throughout the analysis, we interpret City 1 as the local economy and City 2 as the rest of the economy.

C.1 Households

There is a representative consumer in each city with period utility

$$u_{j,t} = \int_{\omega \in \Omega_{j,t}} s_j(\omega) \log\left(q_{j,t}(\omega) + \bar{q}_j\right) d\omega, \tag{4}$$

where $\Omega_{j,t}$ is the set of goods consumed in city j and period t, $q_{j,t}(\omega)$ is the individual consumption of variety ω in city j and period t, and $\bar{q}_j > 0$ is a city-specific constant. There are city-specific tastes, $s_j(\omega)$, such that the demand functions are heterogeneous across goods and cities. Without loss of generality we assume that $\frac{\partial s_1(\omega)}{\partial \omega} \geq 0$ and $\frac{\partial s_2(\omega)}{\partial \omega} \leq 0$. Thus, consumers in City 1 prefer goods closer to $\omega = 1$, while those in City 2 prefer goods closer to $\omega = 0$.

Preferences are non-homothetic, so the demand elasticity changes with income, as in Simonovska (2015). With these preferences the model can be consistent with the empirical findings in Section 4, which show that prices change with income shocks.[36] Moreover, the presence of heterogeneous tastes and non-homotheticity implies that in equilibrium some goods are sold only in City 1, some goods only in City 2, and some in both cities. This characterization is important to capture the empirical finding that some chains are national (i.e., sell in many cities), while others are local (sell only in one city) and can have different responses to regional or aggregate shocks.

The household's problem reads

$$U^j = \max_{q_{j,t}(\omega)} \sum_{t=0}^{\infty} \beta^t u\left(u_{j,t}\right) \qquad \text{s.t.} \qquad \int_{\omega \in \Omega_{j,t}} p_{j,t}(\omega)\, q_{j,t}(\omega) \leq y_{j,t} \qquad \forall t.$$

[35] The model is studied here in partial equilibrium. Our results are robust to extending the model to general equilibrium, with endogenous labor supply and the disutility of labor being the source of shocks (available upon request).

[36] With CES preferences, prices are equal to a constant markup over the marginal cost and therefore prices do not react to income shocks. For more general preferences, see Jung, Simonovska, and Weinberger (2019) or Arkolakis, Costinot, Donaldson, and Rodriguez-Clare (2019), among others.

The demand for variety ω in city j and period t is given by

$$q_{j,t}(\omega) = \max\left\{0, \frac{s_j(\omega)}{\bar{S}_{j,t}} \frac{y_{j,t} + P_{j,t}\bar{q}_j}{p_{j,t}(\omega)} - \bar{q}_j\right\}, \tag{5}$$

where $\bar{S}_{j,t} = \int_{\omega\in\Omega_{j,t}} s_j(\omega)\, d\omega$, and $P_{j,t} = \int_{\omega\in\Omega_{j,t}} p_{j,t}(\omega)\, d\omega$. The marginal utility from consuming a variety ω is bounded from above at any level of consumption. Hence, a consumer may not have positive demand for all varieties.

C.2 Firms

Firms have a linear technology with marginal cost $c_{j,t}$. We compare the solution of two alternative price settings: *uniform* and *flexible pricing*. Under uniform pricing, the firm has to set the same price in both cities; i.e., $p_{1,t}(\omega) = p_{2,t}(\omega) = p_t(\omega)$. Alternatively, under flexible pricing, producers can set different prices in each city.

C.2.1 Flexible Pricing

In the case of flexible pricing, firms can set different prices in each city. The problem of the firm is

$$\max_{p_{j,t}(\omega)} \sum_{j=1}^{J} \left(p_{j,t}(\omega) - c_{j,t}\right) q_{j,t}(\omega)\, M_j$$

taking the demand function (5) as given. The solution is

$$p_{j,t}(\omega) = \left[c_{j,t}\frac{s_j(\omega)}{\bar{S}_{j,t}}\left(\frac{y_{j,t}}{\bar{q}_j} + P_{j,t}\right)\right]^{1/2}. \tag{6}$$

Given the demand function (5) and pricing (6), we can find the set of goods consumed in each city. It is easy to show that this set is characterized by a threshold such that $q_{j,t}(\omega) \geq 0$ if and only if $s_j(\omega) \geq \underline{s}_{j,t}$.[37] The threshold is defined as the taste such that consumption is equal to zero; that is,

$$\underline{s}_{j,t} \equiv \frac{\overline{S}_{j,t}\overline{q}_j c_{j,t}}{w_{j,t} + P_{j,t}\overline{q}_j}. \tag{7}$$

Recall that $s_1(\omega)$ is increasing in ω. Hence, there exists $\underline{\omega}_t \in [0,1]$ such that $q_{1,t}(\omega) \geq 0$ if and only if $\omega \geq \underline{\omega}_t$ and $\underline{\omega}_t = s_1\left(\underline{s}_{1,t}\right)^{-1}$. Similarly, as $s_2(\omega)$ is decreasing in ω, there exists $\overline{\omega}_t \in [0,1]$ such that $q_{2,t}(\omega) \geq 0$ if and only if $\omega \leq \overline{\omega}_t$ and $\overline{\omega}_t = s_2\left(\underline{s}_{2,t}\right)^{-1}$.

[37] To see this, replace the equilibrium price (6) on the demand function (5) and note that it is increasing in $s_j(\omega)$.

C.2.2 Uniform Pricing

Under uniform pricing, each variety ω has the same price in both cities. Therefore, each seller has to choose whether to sell only in City 1, only in City 2, or in both locations. If the seller chooses to sell only in one location, the price function is the same as with flexible pricing. If he sells in both locations, the problem is

$$\max_{p_t(\omega)} \sum_{j=1}^{J} M_j q_{j,t}(\omega)\left(p_t(\omega) - c_{j,t}\right),$$

taking the demand functions (5) as given. The solution is

$$p_t(\omega) = \left[\sum_{j=1}^{2} \frac{M_j}{M_1 + M_2} c_{j,t} \frac{s_j(\omega)}{\bar{S}_{j,t}} \left(\frac{y_{j,t}}{\bar{q}_j} + P_{j,t}\right)\right]^{1/2}. \tag{8}$$

To solve for the set of goods consumed in each city, note that prices are increasing in the taste preference s_j regardless of whether a variety is sold in either one or both cities. This implies that in equilibrium there are thresholds $\underline{s}_{j,t}$ such that in city j the consumption of variety ω is positive if and only if $s_j(\omega) \geq \underline{s}_{j,t}$. Moreover, $s_1(\omega)$ increasing implies that there exists $\underline{\omega}_t$ such that $\Omega_{1,t} = \left[\underline{\omega}_t, 1\right]$. Similarly, as $s_2(\omega)$ is decreasing, then $\Omega_{2,t} = [0, \overline{\omega}_t]$. As a result, the price of variety ω is

$$p_t(\omega) = \begin{cases} \left[c_{2,t}\frac{s_2(\omega)}{\bar{S}_{2,t}}\left(\frac{y_{2,t}}{\bar{q}_2} + P_{2,t}\right)\right]^{1/2} & \text{if } \omega \leq \underline{\omega}_t \\ \left[\sum_{j=1}^{2} \frac{M_j}{M_1+M_2} c_{j,t} \frac{s_j(\omega)}{\bar{S}_{j,t}}\left(\frac{y_{j,t}}{\bar{q}_j} + P_{j,t}\right)\right]^{1/2} & \text{if } \underline{\omega}_t \leq \omega \leq \overline{\omega}_t \\ \left[c_{1,t}\frac{s_1(\omega)}{\bar{S}_{1,t}}\left(\frac{y_{1,t}}{\bar{q}_1} + P_{1,t}\right)\right]^{1/2} & \text{if } \omega \geq \overline{\omega}_t \end{cases}.$$

Finally, the thresholds are defined by

$$\frac{s_1\left(\underline{\omega}_t\right)}{\bar{S}_{1,t}} \frac{y_{1,t} + P_{1,t}\bar{q}_1}{p_t\left(\underline{\omega}_t\right)} = \bar{q}_1 \qquad \text{and} \qquad \frac{s_2\left(\overline{\omega}_t\right)}{\bar{S}_{2,t}} \frac{y_{2,t} + P_{2,t}\bar{q}_2}{p_t\left(\overline{\omega}_t\right)} = \bar{q}_2.$$

C.3 Quantitative Exploration

In this section we quantitatively evaluate the implications of uniform versus flexible pricing.

C.3.1 Calibration

We calibrate the model with uniform pricing in steady state, assuming that City 1 is a representative province of our data and City 2 is the rest of the country. To measure the relative size of a representative province, we use information on the number of stores by provinces. We estimate that the average share of stores that a chain has in a province is 20%. We interpret this as $M_1 = 0.2$ and $M_2 = 0.8$ since those estimates reflect the relative size of the different markets available to a typical chain. We further assume consumers in each city are symmetric, so we set $y_1 = y_2 = 1$ and $\bar{q} = \bar{q}_1 = \bar{q}_2$, and without loss of generality we normalize $c_1 = c_2 = 1$. Moreover, we set the taste parameters $s_1(\omega) = (\omega)^\alpha$ and $s_2(\omega) = (1-\omega)^\alpha$. In Section C.5 we evaluate the role of some of these assumptions in our results.

We calibrate the two preference parameters α and $\bar{q}$ targeting three moments from the empirical results. First, in the data, on average, 7% of stores that sell in a province sell only in that province. In the model, City 1 consumes varieties $\Omega_1 = [\underline{\omega}, 1]$ out of which varieties $[\overline{\omega}, 1]$ are sold only in City 1. Hence, we target this moment as $(1-\overline{\omega}) / (1-\underline{\omega}) = 0.07$.

Section 4.4 shows that prices of firms with a lower local share react less to regional shocks. In the model we define the local share as $local(\omega) = M_1 q_1(\omega) / (M_1 q_1(\omega) + M_2 q_2(\omega))$.[38] We shock the economy with an exogenous increase in income for City 1—we increase y_1 by 1.7%, which corresponds to one standard deviation in the data. We target the response of firms with local shares of 0.5 and 1. Despite its simplicity, the model does a good job at matching the three target moments. Table C5 shows the estimated parameters and target moments.

Table C5: Estimated Parameters and Moments

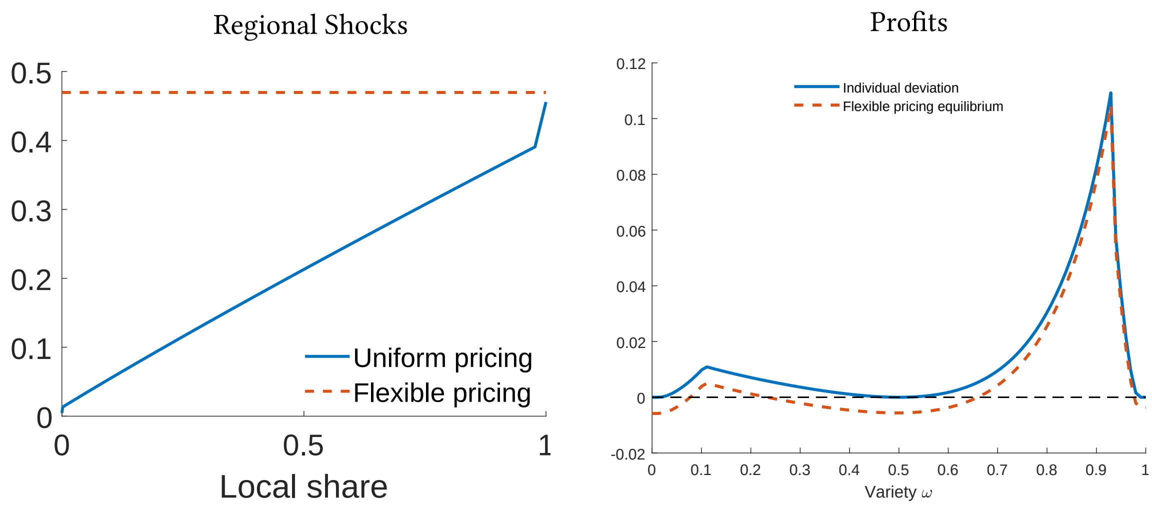
Parameter	Value	Description	Moment	Data	Model
α	1.23	Taste curvature	Local share	7.0	7.0
$\bar{q}$	0.01	Demand constant	Price response p50	0.2	0.2
			Price response p100	0.5	0.5

Notes: The data of price responses and local shares is based on the estimtes of Section 4.4.

Response to regional shocks: In the calibration we target the response of prices to regional shocks for firms with a local share of 50% or 100%. We now compare the response for uniform versus flexible pricing. The first panel of Figure C4 shows the responses of prices to income shocks as a function of the local share. In the economy with flexible pricing, the response of prices is equal to 0.47 for all products regardless of the local share. In the uniform pricing economy, firms have to set the same prices across cities. Hence, when the local share is relatively small, the total demand for that product does not change much. As a result, prices have a small reaction to income shocks. On the other hand, when the local share is high, prices react more to income shocks in City 1. The patterns of price reactions in the uniform-pricing economy resemble the empirical findings of Figure 6, while those in the flexible-pricing model do not.

[38] In the data, we restrict the set of products such that we compare the price of similar goods across stores. Similarly, in the model, we interpret each variety ω as a similar basket sold by different stores.

Figure C4: Uniform vs Flexible Pricing



Notes: The first figure shows the response of prices to regional shocks in City 1. We shock the economy with an exogenous increase in income for City 1; we increase L_1 by 1.7%, which corresponds to 1 standard deviation in the data. The second figure shows the change in profits when the economy moves from uniform to flexible pricing.

Uniform versus flexible pricing: We model uniform pricing as an exogenous constraint to the firm for tractability. We can quantify how costly this constraint is by comparing the profits of firms in this economy with firms in the flexible-pricing economy. The second panel of Figure C4 shows the change in profits when we move from the uniform to the flexible pricing economy. First, the blue solid line shows the change in profits for an individual deviation of only a specific variety ω. In this case the firm can only be better off. Note that for varieties close to $\omega = 0$ and $\omega = 1$ the gains are almost zero. Similarly, at $\omega = 0.5$ the demand elasticities are equivalent in City 1 and 2 and, therefore, there are no gains for firms. The red dotted line shows the change in profits when all firms move to the flexible-pricing equilibrium and so the demand functions also change. In this case there are some winners, those close to the thresholds $\underline{\omega}$ and $\overline{\omega}$ because for those firms the constraint is more costly, while there are some losers, those away from the thresholds. On average, however, the increase in profits is only about 0.35%.

C.4 Aggregate Shocks

We study the responses of prices and consumption to aggregate versus regional income shocks. We define total consumption in city j as $Q_{jt} = \int_0^1 q_{jt}(\omega)\, d\omega$ and a price index $P_{j,t}^{index}$ such that $P_{j,t}^{index} Q_{jt} = \int_0^1 p_{j,t}(\omega)\, q_{jt}(\omega)\, d\omega$. With this decomposition an increase in income y_j is accounted by changes in Q_{jt}

and $P^{index}_{j,t}$. We define the elasticities as

$$\varepsilon_{P,j} = \frac{\Delta P^{index}_{j,t}}{\Delta y_{j,t}} \qquad \varepsilon_{Q,j} = \frac{\Delta Q_{j,t}}{\Delta y_{j,t}}$$

and note that $\varepsilon_{P,j} + \varepsilon_{Q,j} = 1$. With flexible pricing, regional and aggregate shocks have similar effects on prices and quantities. Table C6 shows that the elasticity of prices and consumption are 0.46 and 0.53, respectively, regardless of the type of shock being regional or aggregate.

Under uniform pricing, however, regional and aggregate shocks have different effects. An aggregate shock has almost the same effect as in the flexible-pricing economy. A regional shock, however, has a lower effect on prices and a larger effect on quantities in the uniform-pricing economy. The intuition is that under uniform pricing prices are set accordingly to the total demand of the aggregate economy. If there is a regional shock, the aggregate demand will not change much, and, as a result, prices will be sticky to regional shocks. Consumption, therefore, will react more in the region of the shock than under an aggregate shock in which prices do adjust more. Table C6 shows that when household income increases only in City 1, prices increase by 0.28, while prices increase by 0.44 for an aggregate shock. Thus, consumption increases by 0.71 from a regional shock, while it increases only by 0.55 from an aggregate shock. The estimated model predicts an almost one-third larger elasticity of consumption to a regional income shock than to an aggregate one. This result implies that using regional heterogeneity to infer aggregate elasticities may lead to an upward-bias due to uniform pricing.

Table C6: Regional versus Aggregate Shocks in City 1

	Price index	**Consumption**
Uniform pricing		
Regional shock	0.28	0.71
Aggregate shock	0.44	0.55
Elasticity ratio	0.64	1.29
Flexible pricing		
Regional shock	0.46	0.53
Aggregate shock	0.46	0.53
Elasticity ratio	1.00	1.00

Notes: The table compares the elasticity of the price index and quantities consumed to regional and aggregate shocks in City 1, in the uniform- and flexible-pricing economies. We define the elasticity ratio as elasticity to regional relative to aggregate shocks.

C.5 Alternative City Configurations

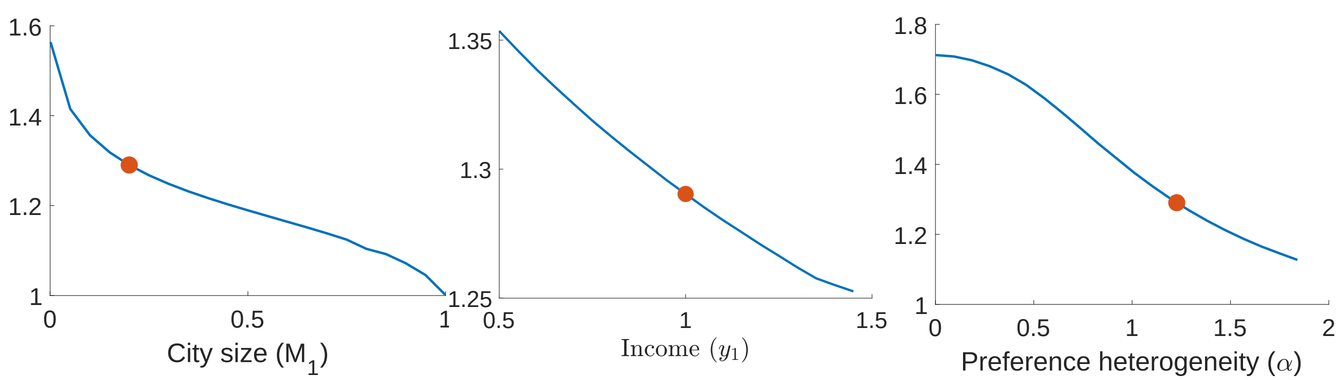
We consider alternative setups to study the quantitative importance of each assumption. We evaluate the effects of city sizes, income, and preferences. We find that the amplification of the response of consumption to regional relative to aggregate shocks is robust to all the alternative specifications.

City Sizes: As City 1 becomes larger, prices will follow more the demand of City 1 and the response of regional and aggregate shocks will become more similar. Figure C5 shows the ratio of the elasticity of consumption to a regional relative to an aggregate shock. In the limit, when $M_1 = 1$ and $M_2 = 0$, the ratio is equal to 1. However, the figure shows that for a wide range of values the ratio is between 1.2 and 1.4 and when M_1 is sufficiently small the ratio can be as high as 1.6. We model the economy as two regions, while in the real world there are many regions, so each city looks like a small region. Hence, this exercise shows that the results would likely be stronger in a larger model that takes geographical heterogeneity into account.

Heterogeneous Income: When City 1 becomes richer the elasticity ratio increases. We vary y_1, which proxy for the income in City 1. The intuition is that under uniform pricing, the seller takes the demand in the richer city more into account and therefore react less to shocks in the poor city. Hence, prices react more to regional shocks in richer than in poorer cities, which decreases the elasticity ratio.

Preference Heterogeneity: When both cities have more similar preferences (lower α), the elasticity ratio increases. The intuition is that for products close to $\omega = 1$ (those with higher preference in region one), the demand from City 1 increases when α decreases. Hence, the prices of those goods will react less to a regional shock, which increases the elasticity ratio.

Figure C5: Alternative City Configurations



Notes: The figures show the change in the ratio of the elasticity of consumption to regional relative to aggregate shocks under alternative parameter configurations.