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Macroeconomic Implications of Uniform Pricing

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Abstract

We compile a new database of grocery prices in Argentina. We find uniform pricing both within and across regions—i.e., prices almost do not vary within stores of a chain. In line with uniform pricing, prices in stores of chains operating in one region react to changes in regional employment, while prices in multi-region chains do not. Using a quantitative regional model with multi-region firms and uniform pricing, we find a one-half 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.

JEL Classifications: D40, E30, L10, R10.
Keywords: Uniform Pricing, Price Dispersion, Regional Economics.

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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; Sufi, Mian, and Rao, 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 inferences about aggregate elasticities.[1] In this paper we explore what the presence of multi-region firms implies for macroeconomics. We first 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. While uniform pricing has been shown to hold in the US, our results suggest that uniform pricing may be a worldwide phenomenon. In line with uniform pricing, we also show that prices tend to react relatively little to local conditions, particularly so for firms that operate in multiple regions. Our main contribution, however, is to build a quantitative model in order 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 than regional 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. One contribution is the creation of a new database for daily posted grocery store prices in Argentina. Since May 2016, every day, stores have to report their offline prices (i.e., prices in the store) to the Argentinean government. The data are 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 important 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

[1] See Chodorow-Reich (2020) for a review of other reasons why the estimated impact of a shock on a single region can differ from the aggregate effect of the shock.

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.[2] 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.[3] Hence, only one-third of the price variation can be explained by stores setting different prices within a chain. While uniform pricing has been shown to be present in the US (DellaVigna and Gentzkow, 2019), we are the first, to the best of our knowledge, to show that this is not just a particular characteristic of the US since it also takes place in the context of a developing country.[4]

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 main 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 multi-region firms of Bernard, Jensen, Redding, and Schott (2018) to incorporate uniform pricing and general equilibrium forces. We map the firms in the model to the twenty-two grocery chains in our data. Regions are mapped to the twenty-four Argentinean provinces, with 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 calibrate the model in steady state. We show, as a validation, that the model is in line with 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 conditions. The estimated model predicts a one-half

[2] 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.

[3] 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.

[4] An additional difference with the US case is that Argentina had high inflation during this period (between 25 and 30% approximately). While we would like to analyze the link between inflation and uniform pricing, inflation during this period in Argentina was not only high but also relatively stable, making it difficult to obtain enough variation to discuss the link between the two. Thus, we do not explore the role of inflation in this paper.

smaller elasticity of prices to a regional shock than to an aggregate one. Thus, it is as if prices are *sticky* to regional shocks, but more responsive to aggregate conditions. 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 in regional elasticities stemming from the variation in regions' sizes and market structures. First, smaller regions have a smaller response to regional shocks because firms setting uniform prices assign less weight to their regional demand and marginal cost, so they react less to regional shocks. Hence, while using smaller regions sometimes is useful in empirical analyses to achieve identification, it is problematic if we want to use that local elasticity as a proxy to the aggregate one. This does not imply that the empirical estimates in the literature are not useful. The estimates are useful to calibrate or validate structural models, as we do in this paper; then, the calibrated model can be used to evaluate the aggregate elasticities (and implications) of the shocks of interest.

The regional market structure also affects the bias between regional and aggregate elasticities. When there are more multi-region firms, prices react less to regional shocks because firms assign less weight to local conditions. Hence, when analyzing empirical regional studies, one should take into account if the relevant price distribution is more likely to be set at the regional or national level, taking the presence of multi-region firms into account.

Uniform pricing also has additional implications. First, it leads to regional shocks having 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. Second, uniform pricing has welfare implications, relative to the alternative of flexible pricing. Households tend to lose when moving to flexible pricing (with an average loss of 0.5%) because uniform pricing prevents firms from extracting more surplus from consumers, but welfare effects are highly heterogeneous, ranging from losses of 3.9% to gains of 0.3%. A large driver of the heterogeneity of welfare effects has to do with the firms' heterogeneous market power across regions. In line with Adams and Williams (2019), we find that in regions where firms have higher market power, welfare losses from moving to flexible pricing are larger.

Finally, in the baseline model we imposed that firms in the grocery sector have to set uniform prices since we are unable to distinguish among various potential reasons for uniform pricing (e.g., operation costs, reputation costs, collusion incentives). We extend the model to incorporate a menu cost so that firms can choose between uniform or flexible pricing. We find that firms would not gain much from setting different prices across regions, so a small fixed cost of adjustment deters firms from discriminating consumers in different regions. Thus, while we cannot distinguish among the various potential reasons for uniform in our data, this exercise shows that a model with small additional costs (whatever their source might be) for flexible pricing should lead to conclusions and quantitative results similar to those from our baseline model.

Related Literature This paper is related to several strands of the literature related to price-setting behavior and its macroeconomic consequences. First, there is a growing 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 these 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.[5] 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.[6]

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 have 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.[7] 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

[5] See also Lach and Tsiddon (1992); Eden (2001); Baharad and Eden (2004) for Israel, Gagnon (2009) for Mexico, Konieczny and Skrzypacz (2005) for Poland, and Borraz and Zipitria (2020) for Uruguay. All of these datasets are much smaller than ours (see data comparisons in Alvarez, Beraja, Gonzalez-Rozada, and Neumeyer, 2018).

[6] 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 their analysis is on narrow categories, without barcodes).

[7] 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*.

(2011), DellaVigna and Gentzkow (2019), Adams and Williams (2019) and Anderson, Rebelo, and Wong (2019) also show that uniform pricing strategies are common in the US.[8] Previous papers, however, used scanner price data, which have 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.

Several papers provide indirect evidence on whether local prices react to local conditions in the US (e.g., Coibion, Gorodnichenko, and Hong, 2015; Beraja, Hurst, and Ospina, 2019; Stroebel and Vavra, 2019; Gagnon and López-Salido, 2019). These papers construct price indexes at the regional level and study how they vary with local conditions (e.g., unemployment, house prices, or labor conflicts). Instead, we do a more granular decomposition by studying prices at the store level, with the novel finding that whether stores are locally or nationally owned is important for the results.[9] Using our precise novel data, we show that prices tend to react relatively little to local labor conditions in Argentina, particularly so for firms that operate in multiple regions—in line with our empirical finding of uniform pricing.[10]

Our main contribution is the study of the macroeconomic implications of uniform pricing. We build on the quantitative literature of multiple regions and sectors (e.g., Caliendo, Parro, Rossi-Hansberg, and Sarte, 2018; Bernard, Jensen, Redding, and Schott, 2018; Hottman, Redding, and Weinstein, 2016) and extend the framework to study multi-region firms setting uniform pricing.

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

[9] This is in line with a series of recent papers that study the effects of local taxes on prices. Baker, Johnson, and Kueng (2021) finds 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). The case of local excise taxes is studied by two recent papers, with opposing results. On the one hand, Butters, Sacks, and Seo (2020) studies the pass-through of excise taxes (mainly on cigarettes) to prices and shows that pass-through rates are similar for national and local chains. On the other hand, Cawley, Frisvold, Hill, and Jones (2020) shows that pass-through of a Philadelphia soda tax into supermarket prices was smaller at chain stores than at independent retailers. While changes in excise taxes can provide clean empirical identification, it is not obvious how to extrapolate these results to other, more relevant goods in the consumption basket because the pricing of these products (e.g., cigarettes) is not typically standard (e.g., prices are not as uniform as for grocery goods), probably precisely because of the differences in local tax policies.

[10] In line with our theory, Kryvtsov and Vincent (2020) finds lack of correlation between the occurrence of sales and economy activity across regions, which may be due to uniform pricing. In a recent paper, Giroud and Mueller (2019) finds that county-level employment is sensitive to shocks in distant counties linked through multi-region firms. Similarly, Garcia-Lembergman (2020) finds that regional prices are sensitive to shocks in distant counties that are served by the same retail chain. Both of these studies support our assumption that multi-region firms operate jointly (with uniform pricing) rather than independently across regions.

Firms' market power matters for price setting as in Atkeson and Burstein (2008). In addition, our uniform pricing extension implies that a firm's local share is also crucial for price setting. Using this framework, 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 conditions.

Our results relate to the growing literature that estimates various elasticities using regional shocks. For example, Mian and Sufi (2011) uses geographical variation to estimate the elasticity of borrowing with respect to house prices. Sufi, Mian, and Rao (2013) uses similar geographical variation to estimate the elasticity of consumption with respect to wealth changes. Given the difficulty of identifying shocks in large regions, this methodology that uses smaller regions to have reasonable control groups has become common (e.g., Autor, Dorn, and Hanson, 2013; Dupor and Guerrero, 2017; Beraja, Hurst, and Ospina, 2019; Yagan, 2019; Mehrotra and Sergeyev, 2021; Stroebel and Vavra, 2019).[11] However, several studies highlight potential sources of differences between local and aggregate elasticities. For example, 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 sources of spillovers such 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. Introducing a novel strategy that can identify aggregate elasticities directly from aggregate shocks (under the assumption of the model being linear), Sarto (2018) finds sizable differences between aggregate and local elasticities—in line with Nakamura and Steinsson (2014). To the best of our knowledge, however, we are the first to highlight that uniform pricing has important implications for this literature. 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.

The rest of the paper is organized as follows. Section 2 introduces our novel price dataset and provides basic descriptive statistics. Section 3 provides our main empirical results regarding uniform

[11] Note these papers do not typically study the elasticity of prices (i.e., our main empirical estimate based on the intuition of uniform prices). Instead, they typically focus on the elasticity of a "quantity" variable like employment or consumption. However, as we show in the model, the elasticities of consumption and of prices with respect to income are directly linked. Due to the budget constraint that links income changes to changes in prices or consumption, a typical model (including ours here) would suggest that if the elasticity of prices is underestimated using regional shocks relative to aggregate ones, the elasticity of consumption would be overestimated.

pricing. Section 4 introduces the model and the macroeconomic implications of uniform pricing. The calibration and quantitative results are in Sections 5 and 6, respectively. Finally, Section 7 concludes. The Appendices contain additional details on the data and model.

2 Data

In February 2016, the Argentinean government passed a normative to build a national, publicly available report of prices (*Sistema Electronico de Publicidad de Precios Argentinos*). The objective of the policy was to reduce inflation by providing information on prices. All large retailers of massively consumed goods have to report daily prices 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.[12]

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 names. We do not know whether these different types of stores operate as different chains, so in parts 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

[12] Online Appendix C.1 shows how the website works. Online Appendix C.2 argues that the data represents the real prices in the stores.

types of sales, we end up with a maximum of three prices per product-store-day.[13] 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 up to 85% of grocery sales in Argentina.[14] 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.[15] Therefore, our empirical analysis assigns equal weight to each product-store included in the analysis.

Balancing these disadvantages, these data has several advantages. First, scanner price data is not easily available outside of developed countries, so our data help fill this gap. Our results suggest that uniform pricing is not only present in the US, but may actually be a more worldwide phenomenon. Second, having daily (instead of weekly or monthly) price data for all products (not just the ones being sold or bought) is an advantage.[16] This is particularly relevant to study uniform pricing, as it allow us to clearly see the posted price and corroborates that prices are in fact identical. Third, with scanner price data it is a challenge to identify temporary sales while we are able to directly observe both the list price and (possibly many) sale prices. While we focus our main analysis on list prices, we show that our two main empirical findings (uniform pricing and the response to regional shocks) are robust to incorporating sale prices. Finally, knowing each store's chain provides us with new information that has not been widely exploited before.[17]

Descriptive Statistics 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 our analysis, we study prices in a particular local market, Buenos

[13] In this paper we focus on list prices but the results are robust to incorporating sales prices; see Appendix A.1.

[14] A large part of the missing stores in our data belongs to the so-called *Supermercados Chinos*. While these stores do not report revenue jointly (and thus appear to be independent of each other), they actually seem to operate in a conglomerated fashion. For example, Sainz (2009) and Federico (2020) argue that these stores buy products and set prices jointly. Even though we cannot observe their prices in our data, in the model, we can evaluate alternative assumptions regarding these stores by changing the share of stores that set uniform pricing in the economy. See Section 6.5.

[15] In the model we account for the relative importance of chains in the consumption basket by using the numbers of stores per chain.

[16] For example, Online Appendix C.4 shows that price-change coordination at the chain level holds at different levels of time aggregation, but is estimated to be stronger the bigger the time window. Thus, this suggests that some price changes take place at a faster frequency than weekly.

[17] Our data also have precise location information on each store (not just zip codes), but we only exploit broader location information in this paper.

Aires City (CABA), as well as in all Argentina, so we provide descriptive statistics for both here.[18] The average province—the "region" definition for most of our empirical and quantitative analysis—in Argentina has 5 chains and 96 stores.[19]

In order to study price dispersion and uniform pricing, 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.[20] Finally, we drop single-store chains to be able to study uniform pricing across stores.[21] Table 1 summarizes the data before and after cleaning, for CABA and Argentina. The data cleaning process eliminates only a few stores. 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.[22] The number of stores per product increases by around 500%, hence allowing us to have enough information to describe price dispersion. The average prices of the products are around 25% lower in the selected sample.

Finally, to measure the effect of our cleaning procedure on uniform pricing we present two measures. First, 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 chain—in the initial sample is very similar to that in the final sample. Second, the average number of unique prices in the raw data is even smaller than in our final, clean data.[23] This suggests that our results are not a feature of our selection procedure, as uniform pricing is just as prevalent in the initial sample.

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.[24]

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

[19]Online Appendix Figure C1 shows the location of all the stores included in the data.

[20]The program *Precios Cuidados* consists of price controls for about 300 products. See Aparicio and Cavallo (2021) for a study of this program.

[21]In the quantitative analysis of Section 5, we keep these single-store chains but this does not change the results since these chains have very small market shares.

[22]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.

[23]This is not surprising since our cleaning procedure eliminates products that are sold at only one chain. This includes chains' own brands, which may be expected to be more likely to set uniform prices.

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

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
Chains per province			5	5
Stores per province			96	96
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
Unique prices by chain-product	2.20	2.86	3.57	5.09

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

3 Empirical Results

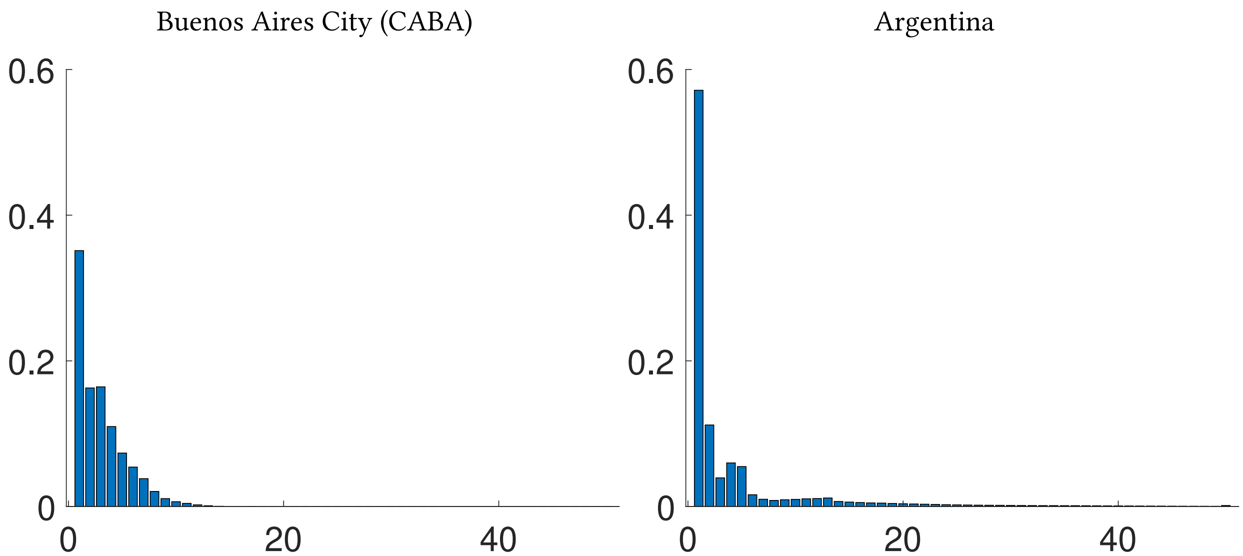
In this section we study the role of chains (as opposed to stores) on prices. We find that conditional on a product, there is little variation across stores of the same chain. We use the term "uniform pricing" to refer to this fact, i.e., that product prices do not vary within stores of a chain. We perform our analysis both using only CABA data and using all national data. In both cases, we show that prices as well as price changes are remarkably similar for all stores within a chain.

One 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.

3.1 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. We study how many different prices each chain sets for their products across stores. The left panel of Figure 1 shows the distribution of unique prices by chain-product observations in CABA. Conditional on a chain, there are only a few prices, much fewer prices than the number of stores. We find that 35% of products have only one price across stores of the same chain and that 70% of products have less than three prices across stores of the same chain.

Figure 1: Unique prices



Notes: Distribution of prices by chain-product.

The right panel of Figure 1 shows that the same result holds when we look at the whole country. We find that 57% of products have only one price across stores of the same chain and that 84% of products have less than five prices across stores of the same chain. We take this result as evidence that chains set the same price across stores.[25]

Uniform pricing is a general characteristic of chains in Argentina. For 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. Table 2 shows that 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%, while price dispersion within chains is on average less than one-third of that. 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, in Online Appendix C.5 we show that the relation between price dispersion and the number of

[25]Online Appendix C.3 shows some case studies of particular products on a particular day. 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).

provinces a chain operates in is positive but relatively flat.[26,27]

Table 2: 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-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-type-province	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 relative (i.e., log-standardized) prices. This measure is explained in detail in the main text.

While observing that a unique price is the mode of Figure 1 is informative, it does not control for the number of stores within a chain. Thus, to compare pricing patterns within- and between-chains more systematically, we introduce two measures of the extent of uniform pricing, similar to DellaVigna and Gentzkow (2019). Each is defined separately for each pair of stores s and s' and goods g. To compute within-chain measures of similarity for good g and chain c; we sample up to 200 pairs of stores $(s; s')$ in chain c, and we average the measures of similarity across all such pairs, using the same pairs for all goods. To compute between-chain measures of similarity for good g and chain c; we follow a similar procedure but draw up to 200 pairs composed of a store s in chain c and a store s' belonging to a different chain c'.[28] Using these pairs, we then calculate two measures. The first measure is the absolute log price difference. For each pair of stores s and s', and good g, we first compute $\log(P_{sg})$ and $\log(P_{s'g})$. We then compute the absolute difference between store s and s'. The second measure is the share of identical prices, defined as the share of observations for which $P_{sg} = P_{s'g}$ for a product g. Figure 2 shows the distribution of these measures, with each good-chain forming one observation. In line with our previous

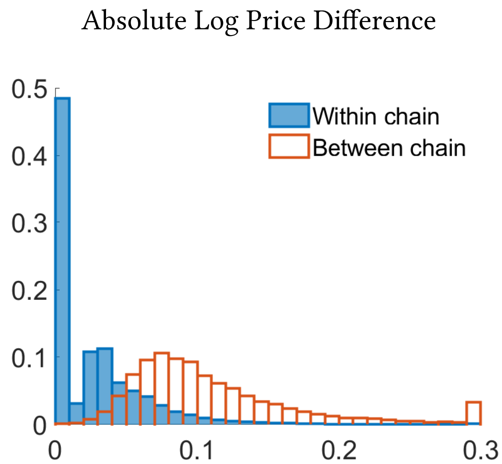
[26] The average number of provinces in which a chain operates is 5.8. The distribution, however, is right skewed, with almost 50% of chains operating in only one province and three chains operating in almost all provinces.

[27] Online Appendix C.3 shows the data at the chain level for both CABA and Argentina.

[28] We focus on a particular day—December 1, 2016—so that we do not have to work with the time dimension, like taking averages or showing the time series properties. Results are similar for different dates.

findings, prices for within-chain pairs (solid bars) are far more similar than for between-chain pairs (hollow bars) on both measures. The absolute log price difference (first panel) is typically below 3 log points for the within-chain pairs, and typically above 12 log points for the latter. The share of identical prices (second Panel) is typically above 0.65 for within-chain pairs, with a large mass point at 1, but is rarely above 0.02 for between-chain pairs.

Figure 2: Similarity in Pricing Across Stores: Same-Chain Comparisons vs Different-Chain Comparisons.



Notes: Each observation in the histograms is a chain-good representing the average relationship between up to 200 store-pairs belonging to each chain on December 1st, 2016. The "same chain" pairs are formed from stores belonging to the same chain; the "different chain" pairs are formed from stores in different chains. The left panel displays the distribution of the average absolute difference in log prices between two stores in a pair, winsorized at 0.3. The second panel displays the share of prices in a pair of stores that are identical to each other.

Price Changes Table 3 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 2.7–2.9% of prices are changed every day, with approximately two-thirds 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, only 13% of other stores in any chain change prices when focusing in CABA, and only 5.5% when looking at Argentina instead. For products that change prices, we observe that around 27–29% 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.[29]

Table 3: 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.

Variance Decomposition 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 average price α_g, a chain average component β_c, a chain-product component $\gamma_{g,c}$, and a residual $\epsilon_{g,s,c}$. In order to reduce the computational requirements and obtain a reasonable normalization (as in Kaplan, Menzio, Rudanko, and Trachter, 2019), this decomposition is done by taking averages in an iterative manner as explained in detail in Appendix A.2. 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 A.2 that allow us to simplify the estimation (which is important given the size of our sample), we can decompose relative price variation in a

[29] Online Appendix C.4 shows that price-change coordination at the chain level also holds when looking at weekly or biweekly data.

chain component, a chain-product component, and the residual:

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

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 for our whole data. Table 4 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. In other words, consistent with Table 2, price variation across stores within chains is small, driving only 27% and 38% of the total relative price dispersion for CABA and Argentina, respectively.[30]

Table 4: Variance Decomposition of Prices

	CABA	**Argentina**
Chain	17	11
Chain-Product	56	51
Chain-Product-Province	0	19
Chain-Product-Province-Store	27	19

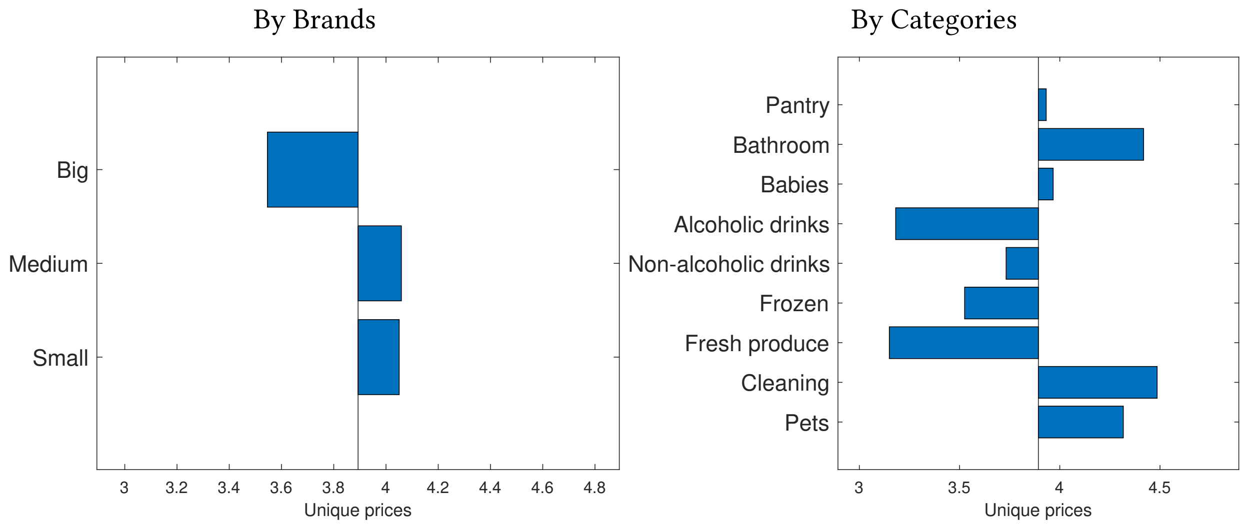
Notes: We perform a variance decomposition of prices to formally highlight the role of chains relative to stores in pricing. See details in Appendix A.2.

Correlation with Product 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.[31] Chains set about 3.9 unique prices per product across stores. The left panel of Figure 3 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.

[30] 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 19% of the 38% remaining price dispersion across stores in Argentina. Appendix A.2 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.

[31] 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 3: 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 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. The right panel shows the number of unique prices according by products' category.

We also find small variation across product categories (as defined by our data source Precios Claros). The right panel of Figure 3 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 pricing is a general property of grocery prices and is not explained by observable product characteristics.

Correlation with Chain Characteristics We also study the relationship between uniform pricing and different chain characteristics. Online Appendix C.5 shows that 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 again, becomes insignificant once we control for the number of types of stores and number of provinces in which a chain operates.

Temporary Discounts Uniform pricing strategies are also present when we take temporary discounts (sale prices) into account. Appendix A.1 shows that there is uniform pricing in sales, which are present for up to 25% of products. This is in line with the discount literature. For example, Kryvtsov and Vincent (2020) finds little evidence that sales co-vary with unemployment across U.K. regions, a finding that they attribute to uniform pricing strategies by large retailers (even though they are not able to observe prices at multiple stores of the same chain). Our results, which do rely on direct observation of sale prices at all stores, confirm their intuition.

3.2 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.[32] 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, $local_{s,t} = N_{c(s),t}^{prov(s)}/N_{c(s),t}$, 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.[33] A chain that is only in one region has $local_{s,t} = 1$, and a multi-region chain has $local_{s,t} < 1$. 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 5 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 5 shows that average-price growth per store is not significantly related to employment growth. 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

[32] We would like to have more precise definitions of labor market conditions, but we are limited by data availability. It is important to highlight that this evidence should not be interpreted as causal. Our model in Section 4 is useful to overcome this limitation. In particular, we use the model to generate and properly evaluate the causal effects of exogenous regional and aggregate shocks. In the quantitative exercise we use the model generated data to estimate the same regression and show that it is in line with this section's empirical findings.

[33] While we allow for the local share $local_{s,t}$ to vary over time, we find its value to be almost unchanged throughout our sample. For example, the mean coefficient of variation by store (across time) is 1.5%. For a store with the average local share of 39.1%, an increase by one (mean) standard deviation would increase its local share to only 39.7%. We also estimated our main regression (1) using non-time-varying measures of local shares and obtained basically the same results.

(i.e., above one-third approximately) while it becomes negative and close to zero for stores with a local share below the median.

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

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

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 4 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 one-standard deviation (3.5%) change in employment growth ($\Delta e_{prov(s),t}$) implies a 1.8% percent change in 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%.[34,35,36]

Table 5: Regional Shocks and Store Prices

	(1) All	(2) Local share < Median	(3) Local share > Median	(4) All	(5) All
Emp. growth ($\Delta e_{prov(s),t}$)	-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)
Store FE	YES	YES	YES	YES	YES
Time FE	NO	NO	NO	NO	YES
Observations	24,626	12,372	12,253	24,626	24,626
R-squared	0.463	0.537	0.425	0.472	0.488

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

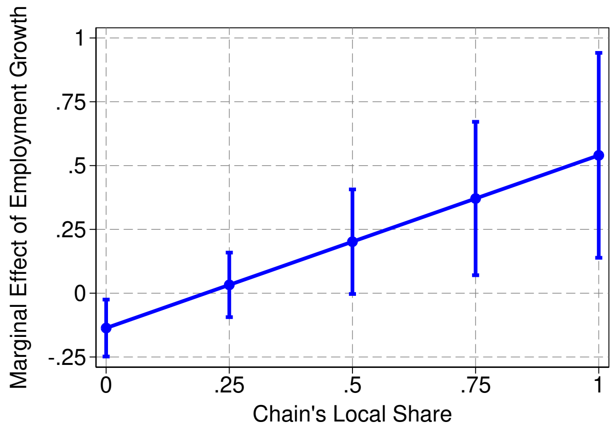
Temporary Discounts The response to local conditions is very similar when we look at list and/or discount prices. Appendix A.1 replicates Table 5 but taking discount prices into account

[34]Figure 4 shows that the marginal effect for stores with local shares near 0% is negative. While this is hard to explain through the lens of a model, we want to highlight that there are very few observations around that point. The share of observations with local shares under 5% is 1.8% and, in fact, it is impossible for firms to have local shares of 0%.

[35]Given that almost 40% of Argentineans live in Buenos Aires province and 29% of the stores are in Buenos Aires, one may worry that Buenos Aires might be driving all of the results. In Appendix C.6, we introduce an extended version of this empirical model that controls for each chains' participation share in Buenos Aires. We do not find any statistically significant differences between the baseline results and the ones focused on chains with low participation in Buenos Aires. Thus, the results are valid for the whole country and not only for Buenos Aires.

[36]As an alternative approach, in Online Appendix C.7 we use an instrumental variable approach akin to Guren, McKay, Nakamura, and Steinsson (2021). While our approach is more limited than theirs (since we do not have as much regional information as they do), it suggests that our main empirical results are robust to introducing sources of plausibly exogenous variation in employment.

Figure 4: 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 5. The vertical lines refer to the 95% confidence intervals.

and finds very similar responses. Prices in stores with larger local shares covary more with local conditions, but almost do not change for chains with small local shares.

To build a model that can explain these findings and study their macroeconomic implications, we first need to understand which type (e.g., demand vs. supply) of shock is being captured by the regression. We find that regional employment and grocery prices move in the same direction, so productivity shocks in the grocery store sector cannot be the drivers of regional variations. If they were, we would expect to see employment and prices move in opposite directions. By contrast, a productivity shock that takes place in another sector of the economy can be the driver. Under this scenario, a positive productivity shock would lead to increased labor demand in the shocked sector, raising both total employment and wages in the region. As wages increase, so do marginal costs for grocery stores, with some pass-through to grocery prices. At the same time household disposable income increases due to the increase in wages, increasing demand of goods. This is the approach we take in this paper's baseline model. Another alternative that can help explain the price changes is a demand shock that affects the demand elasticity. In Online Appendix D we present a simple model following this alternative, where the changes in the demand elasticity are due to income shocks with non-homothetic preferences.

4 Model

We build and estimate a model of heterogeneous regions and sectors with multi-region firms and 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, in the grocery retail sector we add multi-region firms that set uniform prices as documented in the empirical section (i.e., the same price across stores). Second, we introduce endogenous labor supply so regional labor markets are in equilibrium. This implies that wages, and therefore marginal costs, respond to shocks.

There are R regions, $r = 1, \ldots, R$, with three sources of heterogeneity. First, regions differ in size N_r, which we map to population in the data. This allows us to study heterogeneous effects between small and large regions. Second, regional households have heterogeneous preferences across sellers, generating the variation on market shares that we observe in the data. Finally, exports are region-specific and are the source of exogenous regional and aggregate shocks.[37]

In each region there is a representative agent with a nested structure of demand as in Hottman, Redding, and Weinstein (2016). There are three sectors, denoted by $n = 1$, 2, and 3. Sector one corresponds to groceries and is the main focus of our analysis. Sector two aggregates all other nationally produced goods, while sector three represents imported goods. We introduce imported goods so trade is balanced at the regional level. Within each sector there is a continuum of symmetric categories, and within each category there are many firms selling differentiated final consumption goods.

In sectors one and two, firms set prices under monopolistic competition. Sector one has a finite number of firms, mapped directly to the grocery store data. As the data shows a small number of sellers in each region, it is important to assume a finite number of firms. These are multi-region firms, i.e. they sell in many regions, but they have to set the same price across regions (i.e, prices are uniform).[38] Sector two, for simplicity, has a continuum of producers that set different prices across regions (i.e., flexible prices).[39] In sector three, international prices are taken as given.

Our main results are that: (i) firms setting uniform prices weigh each region according to their relative sizes, (ii) regional price elasticities are smaller than aggregate price elasticities, and (iii) regional elasticities are more biased measures of aggregate ones when regions are smaller or firms' sales are more equally distributed across regions.

[37]To replicate the empirical finding in Table 5, this model needs a shock that increases the marginal cost of production in the grocery sector. While any shock that increases wages may be consistent with the data, we use exogenous shocks in the exportable sector because fluctuations in commodity prices are found to be important for emerging economies like Argentina (e.g., Kohn, Leibovici, and Tretvoll, 2021). Another alternative that can help explain the empirical evidence is a demand shock that affects the demand elasticity. We follow this strategy in an alternative simpler model in Online Appendix D.

[38]In the benchmark model, we take uniform pricing as a constraint. Section 6.5 analyzes the implications of a menu-cost model in which firms can pay an adjustment cost to set different prices across regions. We find that for a reasonably small fixed cost firms do not want to set different prices across regions, i.e., the gains from setting different prices across regions are small.

[39]While firms in sector two may also be subject to uniform pricing, we cannot observe this in our data. Thus, our results may be interpreted as a lower bound on the role of uniform pricing.

4.1 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 price index and wages in region r, respectively. The household in region r is the owner of regional profits π_r.[40] We denote by y_r the total income in region r. The optimal labor supply is $\ell_r = (w_r/(\Psi P_r))^{1/\phi}$. Each region is of size N_r, so the total regional labor supply is $L_r^s = N_r \ell_r$.

Demand across sectors Final consumption c_r combines goods from three sectors with a Cobb-Douglas aggregator

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

with $\sum_{n=1}^{3} \lambda^n = 1$. Sector one corresponds to groceries, sector two captures the rest of nationally produced goods, and sector three represents 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 sectoral price index and consumption in sector n, region r, respectively. Households have constant expenditure shares across sectors, λ^n, due to the Cobb-Douglas preferences, i.e., $c_r^n = \lambda^n y_r / P_r^n$, and the price index in region r is $P_r = \prod_{i=n}^{3} \left(P_r^n/\lambda^n\right)^{\lambda^n}$.

Demand within sectors Within each sector there is a continuum of symmetric categories $g \in [0,1]$ with a Cobb-Douglas aggregator

$$\ln\left(c_r^n\right) = \int_0^1 \ln c_{rg}^n dg. \tag{2}$$

For each category g in sector n there are many firms $f \in \Omega_r^n$. In sectors $n = 1,2$, firms set prices under monopolistic competition. Sector one has a finite number of firms while sector two, for simplicity, has a continuum of firms, $\Omega_r^2 = [0,1]$. In sector $n = 3$, import prices are taken as given and normalized to one, $P_{rgf}^n = 1$, for all firms, categories, and regions. Thus, c_{rg}^n is an aggregator

[40] While we would like to justify this assumption using some data, we are unable to observe any evidence on how profits are distributed. One may consider them being sent back to the headquarter's region, distributed according to population, or staying in each region. We followed this last alternative, which may be considered in line with incorporating the return to non-modeled fixed regional factors (e.g., buildings). Moreover, if we were to redistribute profits in a different way we would also be introducing an additional layer of regional externalities, making regional shocks even more different from aggregate shocks.

of consumption from sector n, category g, in region r given by

$$c_{rg}^n = \left[\sum_{f\in\Omega_r^n}\left(\lambda_{rgf}^n c_{rgf}^n\right)^{\frac{\sigma^n-1}{\sigma^n}}\right]^{\frac{\sigma^n}{\sigma^n-1}} \text{ for } n=1, \quad c_{rg}^n = \left[\int_{f\in\Omega_r^n}\left(\lambda_{rgf}^n c_{rgf}^n\right)^{\frac{\sigma^n-1}{\sigma^n}}\right]^{\frac{\sigma^n}{\sigma^n-1}} \text{ for } n\neq 1, \tag{3}$$

where $\sigma^n > 1$ is the elasticity of substitution across firms in sector n and category g. In sector one there is a regional firm's appeal, λ_{rgf}^1, capturing the heterogeneous preferences for firms across regions.[41] Here, c_{rgf}^n is the consumption of goods from firm f in sector n, category g, region r. We allow firms to be large relative to the category (and hence internalize their effects on the consumption and price index for the category). But we assume a continuum of categories so that each firm is of measure zero relative to the economy as a whole (and hence takes total expenditure as given).

The total regional demand is

$$C_{rgf}^n = N_r \lambda^n y_r \left(P_{rgf}^n\right)^{-\sigma^n}\left(\lambda_{rgf}^n P_{rg}^n\right)^{\sigma^n-1}, \tag{4}$$

while the price index in sector n, region r, category g is

$$P_{rg}^n = \left(\sum_{f\in\Omega_{rg}^n}\left(\frac{P_{rgf}^n}{\lambda_{rgf}^n}\right)^{1-\sigma^n}\right)^{\frac{1}{1-\sigma^n}} \text{ for } n=1, \quad P_{rg}^n = \left(\int_{f\in\Omega_{rg}^n}\left(\frac{P_{rgf}^n}{\lambda_{rgf}^n}\right)^{1-\sigma^n}\right)^{\frac{1}{1-\sigma^n}} \text{ for } n\neq 1. \tag{5}$$

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

4.2 Price setting for multi-region firms

The multi-region firm problem is

$$\pi_{gf}^n = \max_{P_{rgf}^n} \sum_{r\in\Omega_{gf}^n} C_{rgf}^n\left(P_{rgf}^n - \delta_{rgf}^n\right),$$

subject to equations (4) and (5), where δ_{rgf}^n is the marginal cost of production. In the benchmark model, firms in sector one (i.e., the focus of our analysis) also have the constraint of uniform pricing, i.e., they have to set the same price in all regions. Firms in sector two, instead, set flexible prices, i.e., they can set different prices across regions. We solve the model both with flexible and uniform pricing to understand the additional effects of the uniform-pricing constraint in the optimal price.[42]

[41] We normalize the geometric mean of firms' appeal equal to one, $\prod_r \prod_{f\in\Omega_r^n} \lambda_{rgf}^n = 1$. Moreover, firms in sectors two and three are homogeneous, i.e., $\lambda_{rgf}^2 = \lambda_{rgf}^3 = 1$.

[42] Section 6.5 solves a menu-cost model in which the firm has to choose between setting uniform prices or paying an adjustment cost to set different prices across regions. The menu-cost extension shows that the constraint of uniform pricing imposes small profit looses relative to an economy without the constraint, suggesting that a relatively small cost of setting flexible prices may be enough to explain why multi-region firms set uniform prices.

Flexible pricing When firms can set different prices across regions there are no direct linkages across regions for a firm, so firms can solve each regional problem independently. In this case, the optimal price is

$$P_{rgf}^{n,flex} = \frac{\left(\sigma^n - (\sigma^n - 1)\, s_{rgf}^n\right) \delta_{rgf}^n}{\sigma^n - (\sigma^n - 1)\, s_{rgf}^n - 1}, \tag{6}$$

where s_{rgf}^n is the market share of firm f, from sector n, category g in region r, i.e.,

$$s_{rgf}^n = \frac{P_{rgf}^n C_{rgf}^n}{\sum_{f'} P_{rgf'}^n C_{rgf'}^n}.$$

This pricing formula is the standard one when market power is taken into account, as in Atkeson and Burstein (2008). If a firm does not have market power (i.e., $s_{rgf}^n = 0$), the price is just a constant markup $\frac{\sigma^n}{\sigma^n - 1}$ over marginal cost δ_{rgf}^n. Alternatively, if a firm does have market power (i.e., $s_{rgf}^n > 0$), the optimal price involves a markup $\frac{\sigma^n - (\sigma^n - 1) s_{rgf}^n}{\sigma^n - (\sigma^n - 1) s_{rgf}^n - 1}$, which is increasing in the firm's market share s_{rgf}^n.

Uniform pricing Now consider a firm that has to set the same price in all regions. The optimal price is

$$P_{gf}^{n,uniform} = \frac{\sum_{r \in \Omega_{gf}^n} \gamma_{rgf}^n \left(\sigma^n - (\sigma^n - 1)\, s_{rgf}^n\right) \delta_{rgf}^n}{\sum_{r \in \Omega_{gf}^n} \gamma_{rgf}^n \left(\sigma^n - (\sigma^n - 1)\, s_{rgf}^n - 1\right)}, \tag{7}$$

where γ_{rgf}^n is the *local share* of region r for firm f, i.e.,

$$\gamma_{rgf}^n = \frac{C_{rgf}^n}{\sum_{r' \in \Omega_{gf}^n} C_{r'gf}^n},$$

which captures how important region r is for firm f.

If a firm is active in only one region (so $\gamma_{r'gf}^n = 1$ only for region r'), the optimal price is the same as with flexible pricing, involving a markup that increases with the market power. Alternatively, if a firm is active in multiple regions, it needs to take into account the market power and the share of sales in each region. A region with a larger share of a firm's total sales will have a larger weight on the firm's pricing decision. This new force appears due to uniform pricing and is the key mechanism to explain the differences in responses to regional shocks across firms with different levels of local shares (as shown in Figure 4). It also generates differences between regional and aggregate shocks as well as spillover across regions.

Response to regional and aggregate shocks The key difference between flexible and uniform pricing is in how they respond to regional changes in marginal cost. Consider the partial equilibrium elasticity of prices to δ^n_{rgf} (i.e., without taking into account changes in market power or local shares). Under flexible pricing, this elasticity is equal to one, so all the increase in marginal costs passes to prices. Under uniform pricing the elasticity is

$$\frac{\partial P^{n,uniform}_{rgf}}{\partial \delta^n_{rgf}} \frac{\delta^n_{rgf}}{P^{n,uniform}_{rgf}} = \frac{Y^n_{rgf}\delta^n_{rgf}\left(\sigma^n - (\sigma^n - 1)\, s^n_{rgf}\right)}{\sum_{r\in\Omega^n_{gf}} Y^n_{rgf}\delta^n_{rgf}\left(\sigma^n - (\sigma^n - 1)\, s^n_{rgf}\right)}.$$

With uniform pricing, instead, the elasticity crucially depends on the local share. If the firm is active in only one region, then the responses under uniform and flexible pricing coincide. When the firm is active in more regions, and assigns less weight to each individual region, the firm responds less to regional changes in marginal costs. In particular, the response is decreasing in the local share, making prices *sticky* to regional shocks.

When the shock is aggregate (i.e., the change in marginal costs occurs in all regions), firms with either flexible or uniform pricing have a full pass-through of marginal costs to prices. Hence, with uniform pricing it is as if prices are *less responsive* to regional shocks than to aggregate conditions, particularly for multi-region firms with small local shares. Thus, uniform pricing makes elasticities to regional shocks different from elasticities to aggregate ones.

Sector two has flexible pricing Finally, as mentioned above, we assume that in sector $n = 2$ there is a continuum of firms (i.e., no market power) setting flexible prices (i.e., one price in each region). Thus, the optimal price in this case is just a constant markup over marginal cost, $P^n_{rgf} = \frac{\sigma^n}{\sigma^n - 1}\delta^n_{rgf}$.

4.3 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 by 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 Producers of intermediate inputs 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 $a^n_{jrfg}(l) = w_j / z^n_{jrfg}(l)$, where $z^n_{jrfg}(l)$ is a stochastic productivity drawn independently for each buyer from a Frechet distribution $G^n_{jrfg}(z) = e^{-T_j z^{-\theta}}$, 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 $G^n_{rfg}(a) = 1 - e^{-\Phi a^{\theta}}$, with $\Phi = \sum_j T_j w_j^{-\theta}$.

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

$$Q^n_{rfg} = \left(\frac{L^n_{rfg}}{\alpha_n}\right)^{\alpha_n} \left(\frac{\int_0^1 I^n_{rfg}(l)^{\frac{\eta-1}{\eta}} dl}{(1-\alpha_n)^{\frac{\eta-1}{\eta}}}\right)^{\frac{(1-\alpha_n)\eta}{\eta-1}}, \tag{8}$$

where α_g is the labor share and $\eta < \theta+1$ is the elasticity of substitution across intermediate inputs. The labor demand is $L^n_{rfg} = Q^n_{rfg}\alpha_n \delta^n_{rgf}/w_r$, where the marginal cost is $\delta^n_{rgf} = w_r^{\alpha_n}\gamma^{1-\alpha_n}(\Phi)^{-\frac{1-\alpha_n}{\theta}}$, where $\gamma = \left(\Gamma\left(\frac{\theta+1-\eta}{\theta}\right)\right)^{\frac{1}{1-\eta}}$. Hence, the marginal cost depends not only on local wages w_r, but also on wages across the country through Φ. There are two key parameters that discipline the spillovers from wages across regions. First, $1-\alpha_n$ captures the share of intermediate inputs in production. If the firm uses more intermediate inputs sourced from across the country, the marginal cost will depend more on national wages. Second, a larger value of θ implies a smaller dispersion of productivity across intermediate producers. Without productivity dispersion, relative wages are the only determinants of the source of intermediate inputs. Thus, when θ is larger, a small change in wages can lead to large changes in regional intermediate inputs, amplifying the spillovers across regions.

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_{jrfg} also corresponds to the share of expenditures on inputs from that source country in its total expenditures on variable inputs.[43]

[43] 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 expenditures on inputs from that source region in its total expenditures on inputs.

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

$$L^{1,int}_{r} = \int_0^1 \left(\sum_{r=1}^{R} \sum_{f\in\Omega^n_{rg}} L^{1,int}_{jrfg}\right) dg \qquad L^{2,int}_{r} = \int_0^1 \left(\sum_{r=1}^{R} \int_{f\in\Omega^n_{rg}} L^{2,int}_{jrfg}\right) dg.$$

As seen in equation (7), our model's implications of uniform pricing are independent of the particular cost function that we assume. However, following Eaton and Kortum (2002) and Bernard, Jensen, Redding, and Schott (2018), we allow for marginal costs to be a composite of local and national (i.e., intermediate) inputs, thus introducing an additional reason why regional and aggregate shocks may also differ in their implications. While we do not need to assume any differences in the production function for firms that operate in different amounts of regions, an alternative model may also allow for that. In particular, we may expect the marginal cost of multi-region firms to use a smaller share of local inputs (e.g., in our model this may be implemented through α_n). While such a model may help interpret uniform pricing as less of a constraint and more of production function characteristic (to be estimated), our main results should be unchanged.[44]

Mapping Model's Goods to the Grocery Sector Data For the sake of clarity, we explain here how we map the model to the data so that we can study the main empirical findings from Section 3. Intermediate inputs, $I^n_{rfg}(l)$, are the products with unique barcodes (e.g., a 2.25 liters *Coca-cola* bottle). Firms in sector $n = 1$, which correspond to the chains in the data, combine these intermediate inputs (from throughout the country) with local labor to produce a basket of grocery products Q^n_{rfg}—indexed by g as shown by equation (8).[45] In equilibrium, these must be equal to c^n_{rgf}. In line with this mapping, we calibrate the share of intermediate inputs $(1-\alpha_1)$ to match the ratio of costs of goods sold to total costs—as explained in Section 5. The model does not incorporate heterogeneous households within each region, so the representative households in each region buys these baskets, c^n_{rgf}, from many firms to build c^n_{rg}, taking into account their prices, preferences and the elasticity of substitution—as detailed by equation (3). We assume that there is a continuum of symmetric categories g, and therefore c^n_{rg}, that are combined to build the

[44]In this alternative model, a regional shock that increases wages in only one region would lead to smaller effects in the marginal cost of multi-regional firms (since their marginal costs are more driven by national conditions) than that of local firms, leading to a smaller change in prices for multi-regional firms. An aggregate shock, instead, would increase marginal costs throughout the country, leading to larger changes in prices for multi-regional firms (and equal to those of firms that operate in few regions).

[45]While we allow for chains' stores to vary across regions in the preference term λ^n_{rgf} (which is mapped to each chain's store presence by region), we abstract from within-region heterogeneity across stores of the same chain.

grocery sector's consumption in each region c_r^n—as in equation (2).[46] Given that all categories are symmetric, we set elasticity of substitution to match the evidence on how much sales of grocery stores change when they adjust their general prices (not just those for one product), as estimated by Hottman (2019).

Exportable Good Each region produces a different exportable good with technology $z_r \left(L_r^x\right)^{\alpha^x}$. This sector takes the international price P_r^* as given, which is the source of regional shocks. The representative firm in this sector solves

$$\pi_r^x = \max_{L_r^x} P_r^* z_r \left(L_r^x\right)^{\alpha_r^x} - w_r L_r^x,$$

with labor demand

$$L_r^x = \left(\frac{P_r^* z_r \alpha_r^x}{w_r}\right)^{\frac{1}{1-\alpha^x}}.$$

A regional shock that increases P_r^* will increase the labor demand for exports in the shocked region, leading to an increase in regional wages. This will then increase marginal costs for final goods producers, which will adjust prices accordingly.

4.4 Equilibrium: Regional labor markets and profits

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

$$L_{rfg}^1 + L_{rfg}^2 + L_r^{1,int} + L_r^{2,int} + L_r^x = L_r.$$

Finally, regional profits (distributed back to the households in the region) correspond to the regional profits generated by the three sectors in region r

$$\pi_r = \frac{1}{N_r}\left(\int_0^1 \left(\sum_{f\in\Omega_{rg}^1} \pi_{rgf}^1\right) dg + \int_0^1 \left(\int_{f\in\Omega_{rg}^2} \pi_{rgf}^2\right) dg + \pi_r^x\right).$$

5 Calibration

We calibrate the model in steady state with uniform pricing in sector one, assuming that model regions represent the 24 Argentinean provinces (the smallest geographic division for which we

[46] While these bundles or categories g can be interpreted as different combinations of products that consumers may buy, the main purpose of having categories g is to simplify the model solution as explained above. We make this assumption so that firms do not internalize that their choices affect the price index in the economy P_r, but they do internalize that they affect the category price index P_{rg}^n (which we interpret as the price index for groceries since all categories are symmetric) due to monopolistic competition.

have employment data), mapping firms in sector one to chains in our data. We calibrate most of the parameters externally (i.e., without simulating the model), except for one parameter for which we have to use a simulated method of moments. Table 6 shows the parameters together with their sources or estimated moments.

Table 6: Estimated Parameters and Moments

Parameter	**Value**	**Description**	**Moment**	**Data**	**Model**
α_1	0.41	Local labor share of production ($n = 1$)	Cost of Goods Share (Balance Sheet)	0.59	0.59
α_2	0.66	Labor share of production ($n = 2$)	Labor share	0.66	0.66
α_x	0.66	Labor share of production (exports)	Labor share	0.66	0.66
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%
θ	4	Int. inputs: Frechet shape	Productivity distribution (Simonovska and Waugh 2014)		
η	3	Substitutability between int. inputs			
N_r	See Figure 5	Region's available labor	Provincial population shares of country (Census)		
$\lambda_{rgf}^{n,F}$	See Figure 5	Preferences for chains	Store distributions by province		
λ_i	{.3, .6, .1}	Consumption expenditure shares	CPI consumption basket shares		
ϕ	1	Labor disutility	Frisch elasticity	1	1
Ψ	1.32	Labor disutility	Share of time working	0.35	0.35

Notes: See text for details.

First, we calibrate the share of intermediate inputs in the final production of the grocery sector. One of the firms in our data (*La Anonima*) is a publicly-traded company so we have access to its financial reports, from which we estimate $\alpha_1 = 0.41$.[47] Regarding the other two sectors, we set $\alpha_2 = \alpha_x = 0.66$ so that the labor share in the exporting sector and in the final goods sector are equal to 0.66.

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 Appendix B.4, 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 $\sigma^1 = 4.5$.[48] 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 $\sigma^2 = 7.66$.

Regarding intermediate inputs, we need to calibrate the productivity distribution , as defined by Frechet shape parameter θ, as well as the substitutability between inputs, as defined by η. We set

[47] The 2018 financial report indicates that the cost of goods sold was \$36.9bn while the total cost (which also includes commercialization and administration costs) was \$62.6bn. Thus, we estimate the share of intermediate inputs $(1 - \alpha_1)$ as $\frac{36.9}{62.6} = 0.59$. Based on Safeway and Walmart financial reports, Stroebel and Vavra (2019) estimate the share of intermediate inputs in US grocery stores to be about 25%. Section 6.5 shows that our main results are robust to using this alternative lower value of α_1 (as well as an alternative higher one).

[48] The estimated model implies an average markup in sector one of 40.8%. 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%.

$\theta = 4$ based on recent estimates from the trade literature by Simonovska and Waugh (2014). This is also in line with the literature review by Head and Mayer (2014), who, based on the estimates of 32 papers, find an average estimate of θ of 4.5 and a median estimate of 3.2.[49] We also set $\eta = 3$, which satisfies the condition $\eta < \theta + 1$. This value has no quantitative role in our results, as shown in Appendix B.4. We measure the relative size of each province N_r using the population by province. We map the firms in sector one 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 $\lambda^{n,F}_{rf}$.[50]

Figure 5 shows the population of each province as well as the estimated market share of each chain in each province, highlighting the heterogeneity across firms and regions in the data. Note that we have both multi-region chains that are in almost every region, as well as more local chains that are only in one or two regions. This heterogeneity is important to measure how uniform pricing across regions affects the aggregate economy.

We calibrate T_r and z_r such that if regions are identical except for the size of their populations, regions also have the same equilibrium wages and sector shares. Hence, we set $T_r = N_r$ and $z_r = \bar{z}_r N_r^{1-\alpha^x}$. We also set $\bar{z}_r$ such that in steady state trade is balanced at the regional level.[51]

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.[52] Finally, we set the Frisch

[49] θ also 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 take place. Using the regional shocks explained in Section 5.1, we estimate the own-wage elasticity (i.e., the ratio of the percent change in non-export labor to the percent change in wages). In the estimated model, we find an elasticity of -0.69, which is in line with the empirical estimates as summarized by Lichter, Peichl, and Siegloch (2015). They report an average elasticity estimate of -0.55, with a standard deviation of 0.747 and 83% of estimates within the interval of minus one and zero.

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

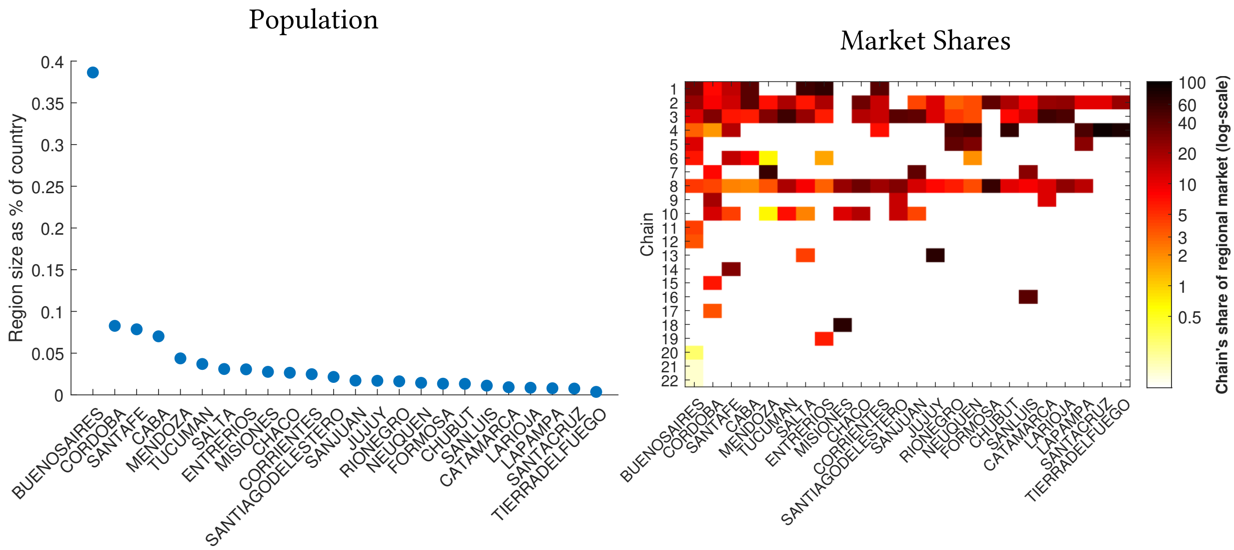
$$\lambda^{n,F}_{rf} = \left(s^n_{rgf}\right)^{\frac{1}{\sigma^n - 1}} P^{n,F}_{rgf}\left(\left\{s^n_{rgf}, w_r\right\}\right),$$

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).

[51] When we introduce regional shocks in the following sections, trade is no longer balanced at the regional level but it is balanced at the national level.

[52] 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,

Figure 5: Population sizes and market shares



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

elasticity of labor supply $1/\phi$ to 1 (as in Kaplan, Moll, and Violante 2018 or Blundell, Pistaferri, and Saporta-Eksten 2016) and the weight on the labor supply component of utility, Ψ, is set (using simulated method of moments) so that the share of hours worked is equal to 35% in steady state.

5.1 Validation

Firms charge different prices because each firm internalizes the effects of its pricing decisions on market price indexes and these effects are greater for larger firms. This feature is based on Atkeson and Burstein (2008) and has been widely used in the trade literature (e.g., Edmond, Midrigan, and Xu, 2015) and in the non-trade pricing literature (e.g., Hottman, Redding, and Weinstein, 2016). Uniform pricing introduces a role for the local share γ^n_{rgf} in the pricing decision as shown in equation (5). Note that γ^n_{rgf} only changes the relative weights of each region for each firm's pricing decision. The effect on prices is unclear since it depends on whether the regions with higher γ^n_{rgf} are those with higher/lower marginal costs, δ^n_{rgf}, and whether the firm has higher/lower market power, s^n_{rgf}, in those regions. An increase in the marginal cost, however, should be associated with larger price increases for the firms with higher local share γ^n_{rgf}. We now check that this novel mechanism is quantitatively in line with the empirical evidence from Figure 4.

communication, entertainment, education, restaurants and hotels are nationally produced goods (i.e., sector two in our model). This leaves the clothing sector (of about 10% of expenditures) that we assume refers to imported goods (i.e., sector three). 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 Appendix B.4 we evaluate the sensitivity of our results to alternative estimations.

Section 3.2 shows that prices of firms with a lower local share react less to regional shocks. As a validation exercise, we now check that the model is in line with the empirical estimates from the data.[53] 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 store prices (constructed using $P_{gf}^n = P_f^n$ for $n = 1$ from equation (7)) for all regions after each regional shock and estimate a regression equivalent to the one done in the data (see equation 1) with store fixed effects.[54]

Figure 6 shows that the marginal effect of employment growth on prices for chains with different levels of local shares in the model is within the 95% confidence bounds estimated in the data (see Figure 4).[55] This suggests that our estimated model is not only qualitatively but also quantitatively in line with the empirical finding that multi-regional firms react less to local shocks.

6 Quantitative Results

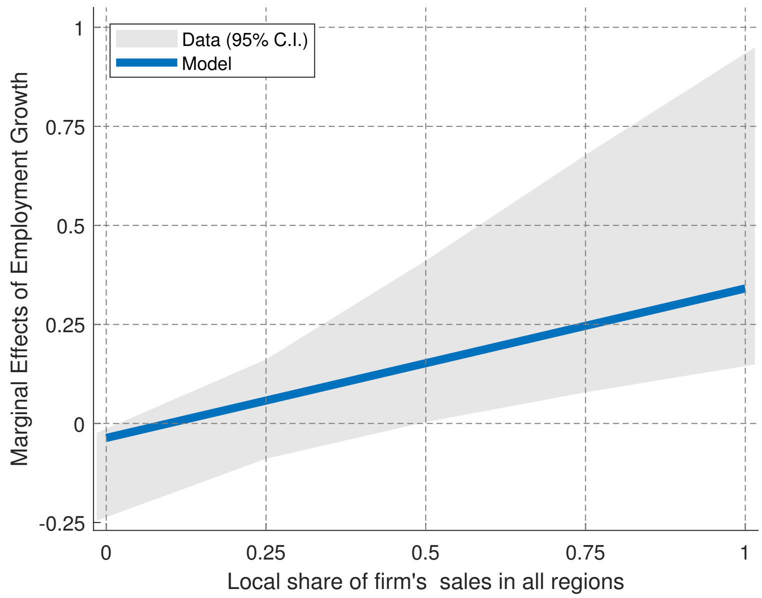
We now quantify how the presence of uniform pricing makes regional elasticities different from aggregate ones. In Section 6.1 we show that uniform pricing is necessary to explain the empirical finding that prices in the grocery store sector react more to regional shocks when a firm's local share is high. We also show that for aggregate shocks, the price elasticity is independent of local shares and larger than when shocks are regional. Section 6.2 summarizes our main result that the total price regional elasticity is one-half of the aggregate one and decomposes the sources behind this difference. In Section 6.3, we exploit the heterogeneity in regional elasticities to show that using regional elasticities to estimate aggregate elasticities may lead to a larger bias when regions are small or firms' are multi-regional. In Section 6.4, we use model-generated data to replicate empirical studies that estimate elasticities using regional variation and show the additional difficulties that uniform pricing introduces. Finally, Section 6.5 provides additional results and extensions.

[53]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 category g as a similar basket sold by different firms f. So, we map the local share in the data with γ_{rgf}^n in the model.

[54]Given that we have 24 regions (provinces) and 119 unique chain-province combinations in our estimated model, we have $119 \times 24 = 2,856$ model-generated points for our model regression—in which we implement store fixed effects as chain-province fixed effects.

[55]Appendix Table B1 shows the estimated coefficients. It also shows that the regression with shock-source fixed effects, which are similar to time fixed effects in the empirical regressions, are similar in the model and data. In particular, the coefficient regarding the interaction between employment growth and local share in the model is 0.430 in the model, very similar to the estimated value of 0.454 in the data.

Figure 6: Validation



Notes: We shock the simulated model 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. We then estimate (1) as in the data. In particular, we include store fixed effects as in Figure 4 and column 5 of Table 5.

6.1 Uniform Pricing

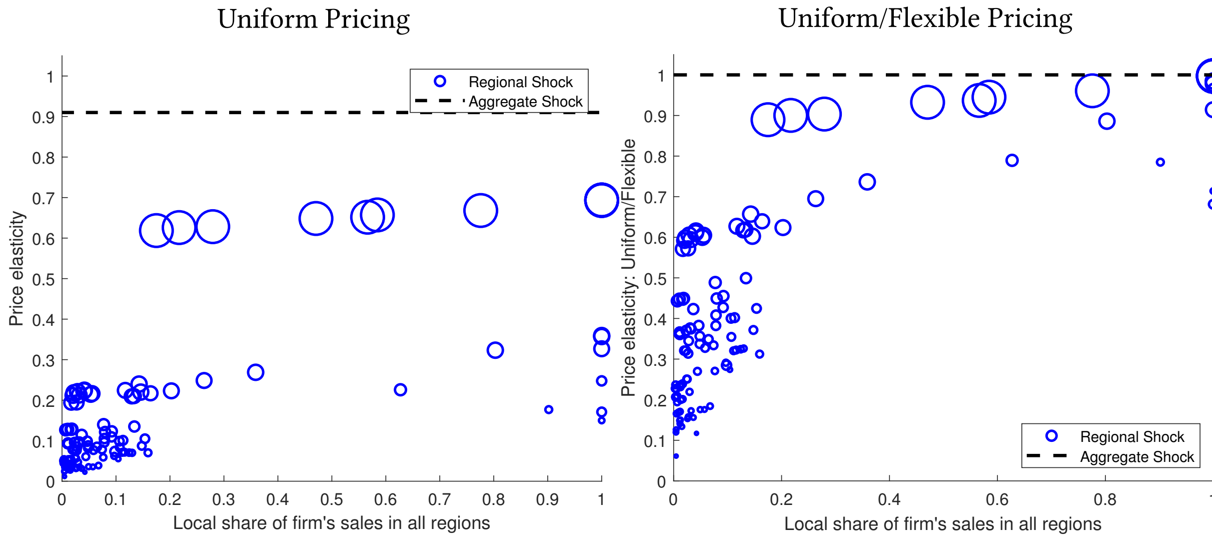
We study how firms in the grocery sector (i.e., sector one), which set uniform prices, respond to aggregate versus regional shocks. A regional shock, as in the validation, refers to an increase in the price of the exportable good P^*_r for a single region r. An aggregate shock, instead, refers to an increase in P^*_r for all regions r.[56] These shocks increase labor demand for exports, leading to increased employment, wages and income. We now use notation Y_r for regional income in region r to highlight that it is a variable at the regional level (and not at the household level), but $Y_r = y_r$ because there is a representative agent in each region. We then calculate the elasticity of prices (for each firm) to the regional income: $\varepsilon_{P^n_{rgf},Y_r} = \frac{\Delta \log\left(P^n_{rgf}\right)}{\Delta \log(Y_r)}$.

Uniform vs. Flexible Pricing We now solve a counterfactual model in which firms in sector one can set flexible prices. For each firm in sector one, we calculate the price elasticity, $\varepsilon_{P^n_{tgf},Y_r}$, with uniform and flexible pricing. The left panel of Figure 7 shows that the elasticity $\varepsilon_{P^n_{tgf},Y_r}$ with uniform pricing, as a function of a firm's local share. The right panel shows the ratio of the two, i.e., the elasticity under uniform pricing divided by the elasticity under flexible pricing. The price reaction to regional shocks is much lower with uniform pricing than with flexible pricing

[56] As in the validation, we increase P^*_r by 4.43%, which corresponds to one standard deviation of export commodities prices in the data. In Appendix B.4, we show that our main result is almost unchanged if we change the size of the shock.

when the local share is small—e.g., the ratio is between 0.1 and 0.65 when the local share is below 0.2. 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. By contrast, in the economy with flexible pricing, the response of prices is the same for all firms regardless of the local share.[57] Thus, the patterns of price reactions in the uniform-pricing economy resemble the empirical findings of Figure 4, while those in the flexible-pricing model do not.

Figure 7: 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 left panel shows the response of prices to regional and aggregate shocks under uniform pricing. The right panel shows the response of prices of each store to regional and aggregate shocks under uniform pricing divided the response under flexible pricing. For example, a coefficient of 0.5 means that the store's price elasticity under uniform pricing if 50% that of the same store under 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 the left panel of Figure 7 shows $\varepsilon_{P^n_{rgf}, Y_r}$ when the shocks are aggregate (i.e., the same shock takes place in all regions), under uniform pricing. 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, which leads to price increases that are independent of local shares. It is also clear that aggregate shocks lead to larger price changes than regional shocks, particularly when the regional shocks take place in

[57] See equation (6). With flexible pricing, prices depend only on market shares and marginal costs (i.e., not on local shares). Thus, an export shock that increases marginal costs and regional income has the same effect for all firms that sell in the shocked region.

regions in which firms have small local shares. For example, firms with local shares around 0.1 display a price elasticity of approximately 0.05–0.2 when the shock is regional but an elasticity of 0.9 when the shock is aggregate. For firms that are only in one region (i.e., local share of 1), the price elasticity is between 0.2 and 0.7 when the shock is regional but is 0.9 when the shock is aggregate. The dotted line in the right panel of Figure 7 shows, instead, that the price reaction to an aggregate shock is the same under flexible and uniform pricing.

Price elasticities are heterogeneous because of firms' local shares as well as regions' sizes. Regions' sizes, as shown by the size of the circles in Figure 7, 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.

6.2 Regional vs Aggregate Elasticities

Our main quantitative contribution is to study how the overall economy responds to regional versus aggregate shocks in the presence of uniform pricing. To summarize these results, we study the responses of the sectoral price index P_r^n, price index P_r, and consumption C_r to shocks. We define the elasticities as

$$\varepsilon_{P_r^n,Y_r} = \frac{\Delta \log\left(P_r^n\right)}{\Delta \log\left(Y_r\right)}, \qquad \varepsilon_{P_r,Y_r} = \frac{\Delta \log\left(P_r\right)}{\Delta \log\left(Y_r\right)}, \qquad \varepsilon_{C_r,Y_r} = \frac{\Delta \log\left(C_r\right)}{\Delta \log\left(Y_r\right)}, \tag{9}$$

and note that $\varepsilon_{P_r,Y_r} + \varepsilon_{C_r,Y_r} = 1$. Table 7 reports the population-weighted average across regions for these elasticities under different scenarios. Panel (a) shows that, under the baseline economy of uniform pricing with endogenous intermediate inputs, the price elasticity ε_{P_r,Y_r} is 0.41 when the shock is regional, but it is 0.82 when the shock is aggregate. The elasticity ratio of regional to aggregate shocks, our main measure of elasticity differences, is $\frac{0.41}{0.82} = 0.50$. In other words, the estimated model predicts a one-half smaller price elasticity to a regional shock than to an aggregate one.

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 7 also reports the consumption elasticity. To compensate for the differences in the price elasticity, the consumption elasticity is 0.59 when the shock is regional, but it is 0.18 when the shock is aggregate.[58]

[58] An alternative way to estimate the price elasticity is to regress $\Delta \log\left(P_r\right)$ on $\Delta \log\left(Y_r\right)$, using data from all regions. This methodology, which is closer to the analysis in empirical regional papers, is explored in Section 6.4.

The model has two forces generating regional elasticities different from aggregate ones: uniform pricing and intermediate inputs. We analyze the quantitative importance of each force. Panel (c) of Table 7 shows that when these two elements are shut down (i.e., prices are flexible, and the cost and 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. Panel (b) of Table 7 shows that with uniform pricing but fixed intermediate inputs, the price elasticity ratio is 0.83. Given the baseline value of 0.50, this suggests that uniform pricing generates about one-third of the difference (i.e., $1-0.83 = 0.17$ of a total of $1-0.50 = 0.50$) 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.

Table 7: Regional versus Aggregate Shocks

	Prices				Consumption
	Groceries (P_r^1)	Other (P_r^2)	Imported (P_r^3)	Index (P_r)	Aggregator (C_r)
(a) Uniform pricing					
Regional	0.35	0.51	0.00	0.41	0.59
Aggregate	0.91	0.91	0.00	0.82	0.18
Elasticity ratio	0.38	0.56	1.00	0.50	3.32
(b) Uniform pricing + fixing intermediate inputs					
Regional	0.09	0.41	0.00	0.27	0.72
Aggregate	0.26	0.42	0.00	0.33	0.66
Elasticity ratio	0.33	0.98	1.00	0.83	1.09
(c) Flexible pricing + fixing intermediate inputs					
Regional	0.26	0.42	0.00	0.33	0.66
Aggregate	0.26	0.42	0.00	0.33	0.66
Elasticity ratio	1.00	1.00	1.00	1.00	1.00

Notes: The table evaluates the elasticity of the sectoral price index P_r^n for each sector $n = \{1, 2, 3\}$, price index P_r, and regional consumption C_r, to regional and aggregate shocks. Panel (a) refers to the uniform-pricing economy with endogenous intermediate inputs (baseline); panel (b) to uniform-pricing with fixed intermediate inputs; and panel (c) to flexible-pricing with fixed intermediate inputs. We define the elasticity ratio as elasticity to regional relative to aggregate shocks.

The regional price elasticity in our a model is composed of the sectoral price indices P_r^n in the sectors $n = \{1, 2, 3\}$. The first three columns of Table 7 show the elasticity and elasticity ratios for each of these sectors. The elasticity ratio is 0.38 in the grocery store sector ($n = 1$), while it is 0.56 for other nationally produced goods ($n = 2$) . Prices for imported goods ($n = 3$), instead, don't change with regional or national conditions, so the elasticity is zero for both regional and aggregate shocks, and its sectoral elasticity ratio is 1 (i.e., no bias). The elasticity ratio bias is the largest in sector one since this is the only one for which we assume uniform pricing. However, it may be reasonable to expect other sectors of the economy with multi-region firms (e.g., online shopping, clothing retailers or many others) to also have uniform pricing strategies across regions.[59] By comparing the elasticity ratios in panels (a) and (b), it is seen that intermediate inputs explain most of the elasticity differences in sector two, while uniform pricing is the main driver in sector one. Given that sector two is estimated to be about 60% of the economy, introducing uniform pricing in parts of this sector may substantially increase the differences between price elasticities to regional vs. aggregate shocks. Hence, our estimate of the elasticity bias may be interpreted as a lower bound.

6.3 What factors generate larger biases in regional elasticities?

Figure 7 shows that firms' price elasticities in sector one are heterogeneous because of market structure as well as regions' sizes. We now study how the price index elasticity ε_{P_r,Y_r} and consumption elasticity ε_{C_r,Y_r}, as defined in equation (9), differ across regions and generate biases when estimating the aggregate elasticities. We regress the elasticities on the region's size (N_r) and market-share weighted-average local share $\left(\gamma_r = \sum_{f\in\Omega_r^n} s_{rgf}^n \gamma_{rgf}^n \text{ for } n = 1\right)$,

$$\text{Regional Elasticity}_r = \alpha_0 + \alpha_1 N_r + \alpha_2 \gamma_r + \varepsilon_r,$$

where $\text{Regional Elasticity}_r = \left\{\varepsilon_{P_r,Y_r}, \varepsilon_{C_r,Y_r}\right\}$. Table 8 shows the results using both price and consumption elasticities.

Table 8: Regional Elasticity Heterogeneity

	Price elasticity	Consumption elasticity
Avg. local share	0.0583	-0.0589
	(0.0206)	(0.0208)
Market size	1.1049	-1.1148
	(0.0558)	(0.0564)
R^2	0.96	0.96
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.

Size When the regional shock takes place in a smaller region the bias is larger. Sellers put less weight on local conditions of small regions. Hence, prices are stickier and the responses to regional and aggregate shocks become more different.

[59]For example, see Cavallo, Neiman, and Rigobon (2015) for uniform pricing in clothing, or Adams and Williams (2019) for the retail home-improvement industry.

This result shows a potential conflict between the econometrician and the macroeconomist. On the one-hand, for some empirical applications it is important to have data of small regional units (e.g., at the zip code level) to achieve identification. On the other-hand, as regions become smaller, the bias due to uniform pricing is enlarged and it makes difficult its macroeconomic interpretation. Hence, our result implies that practitioners should take into account the size of the regions when performing cross-regional analysis, particularly if in the market under study prices are uniform across regions.

Market Structure There is a larger bias when there are more multi-region firms (i.e., the average local share is small). When firms sell in many regions, they respond less to local conditions. Hence, regional prices react less to regional variation, which increases the differences between regional and aggregate elasticities.

This result is important given the rise in concentration and multi-region firms (Rossi-Hansberg, Sarte, and Trachter, 2018). As the market structure changedtoward an increasing number of multi-region firms, the bias due to uniform pricing should be larger now than in the past. Moreover, if we were to use cross-regional variation over two different time periods (e.g., 1990 vs. 2020), the results would be contaminated by the change in the bias.

6.4 Replicating Empirical Studies

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 analysis in regional empirical papers. For example, Sufi, Mian, and Rao (2013) uses geographical variation (where shocks are assumed to be driven by house prices) to estimate the elasticity of consumption with respect to wealth changes. Given the difficulty of identifying shocks in large regions, this methodology tends to prefer using smaller regions in order to have reasonable control groups. To implement this in our model, we use the data on prices P_r and Y_r from our model-generated shocks. While we do not use any instrument in our model regression (as many empirical papers do), we are able to perfectly calculate the elasticities in the model since we can generate and identify the shocks. Given that we have 24 regions (provinces), we have 576 model-generated observations (24 potential source of regional shocks times 24 regions in which we observe their impact on prices and income) for our model regression. Using this model-generated data, we estimate

$$\Delta \log\left(P_{r,t}\right) = \alpha + \beta \Delta \log\left(Y_{r,t}\right) + \theta_t + \varepsilon_{r,t},$$

where θ_t is a shock-source fixed effect (similar to time fixed effects in empirical regressions).

Using this methodology (and weighting regions by population size) and our model-generated regional shocks, Panel (b) of Table 9 shows that we estimate an average price elasticity of 0.62.

Including shock-source fixed effects, the elasticity estimate is reduced to 0.18. The actual average elasticity in our model is 0.41, as shown in Panel (a), so within this range of regression estimates, but it is not equal to either of them. In line with Guren, McKay, Nakamura, and Steinsson (2020), who show that time fixed effects absorb GE effects, we find that the fixed-effects regression is actually closer to the exact regional elasticity in our model for small regions (i.e., 0.23), which are the regions with the smallest spillover and aggregate effects. By contrast, the regression without time fixed effects is actually closer to both the exact regional elasticity in our model for large regions (i.e., 0.62 vs. 0.52) and the exact aggregate elasticity (i.e., 0.62 vs. 0.82), i.e., the regions with the largest spillover and aggregate effects.

Table 9: Empirical Regressions vs. Elasticity Estimates

	(1) Uniform pricing			**(2) Flexible Pricing + Fixed int. inputs**		
	All Regions	Small	Large	All Regions	Small	Large
			(a) Exact Elasticity			
Regional Shock	0.41	0.23	0.52	0.33	0.33	0.33
Aggregate Shock	0.82	0.82	0.82	0.33	0.33	0.33
		(b) Based on Regression of $\Delta \log(P_r)$ on $\Delta \log(Y_r)$				
Without FEs	0.62	0.57	0.57	0.33	0.33	0.33
	(0.01)	(0.07)	(0.07)	(0.00)	(0.00)	(0.00)
With FEs	0.18	0.18	0.18	0.33	0.33	0.33
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Notes: We introduce regional shocks to the economy as an exogenous increase in the 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. We introduce an aggregate shock as an increase in the price of exports for all regions. Panel (a) shows the elasticity of the price index to regional and aggregate shocks. Panel (b) shows the estimates for the price elasticity based on regressing $\Delta \log(P_r)$ on $\Delta \log(Y_r)$, using the regional shocks from all regions and weighting regions by population size. We include shock-source fixed effects, which are similar to time fixed effects in empirical regressions. The left side (1) of the table refers to the uniform-pricing economy with endogenous intermediate inputs (baseline); the right side (2) to flexible-pricing with fixed intermediate inputs. Large regions are defined as the regions with more than 5% of the national population. These include only four regions, which amount to 62% of Argentina's population. Small regions are defined as all the remaining provinces.

These results highlight a conflict between the econometrician and the macroeconomist when trying to use regional variation to estimate aggregate elasticities. To obtain identification, the econometrician requires using small regions and time fixed effects. To be closer to aggregate elasticity estimates, however, the macroeconomist requires larger regions and no time fixed effects. If we were to abstract from uniform pricing and endogenous intermediate inputs that are traded across regions, the right side of Table 9 shows that these empirical regressions actually do a perfect job at estimating the elasticities. The presence of cross-regional spillovers (through uniform pricing and intermediate inputs) implies that it is not possible to use regional variation to estimate aggregate elasticities. This does not imply that the empirical estimates in the literature are not useful. The estimates are useful to calibrate or validate structural models, as we do in this paper; then, the calibrated model can be used to evaluate the aggregate elasticities (and implications) of the shocks of interest.

6.5 Additional Results

Spillovers Uniform pricing also implies that shocks in one region have spillover effects on other regions. On average, a regional shock makes prices in other regions increase by 4.0% relative to the increase in prices if the shock were an aggregate one. Similarly, consumption falls by -0.9% relative to the change due to an aggregate shock.[60] But spillover effects are heterogeneous, depending on where the shock takes place. A shock in Buenos Aires province, the largest region, leads to an average increase in prices of approximately 37% (relative to the aggregate shock) in the other regions. This then causes an average decrease in consumption of 7% (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.

Welfare: To evaluate the welfare implications of uniform pricing for regional households, we compute the welfare gains (in consumption equivalent units) of moving from uniform to flexible pricing in each region. Households tend to lose when moving to flexible pricing (with an average loss of 0.5%) because uniform pricing prevents firms from extracting more surplus from consumers, but welfare effects are highly heterogeneous, ranging from losses of 3.9% to gains of 0.3%.[61] A large driver of the heterogeneity of welfare effects has to do with the firms' heterogeneous market power across regions. Households care about what prices would be if firms, instead of setting a uniform price, were able to set different prices in each region. In our model, firms set higher prices when they have higher market power. Thus, if firms have heterogeneous levels of market power across regions, they would want to increase prices in regions where they have more market power. In line with Adams and Williams (2019), chains that operate in low-competition regions need to take into account that increasing prices may increase local profits but would also lead to large profit losses in high-competition regions.

Parameter Sensitivity: One of the key parameters in the model is the share of local labor and intermediate inputs in sector one. We show two alternative calibrations (with re-estimated Ψ). In the second column of Table 10 we set a lower value of $\alpha_1 = 0.25$ which corresponds to the value reported for the US.[62] In the third column we consider a higher value and set $\alpha_1 = 0.66$. We interpret these alternative calibrations as lower and upper bounds of α_1, respectively.

[60] Appendix B.2 shows the details and also decomposes the spillovers due to uniform pricing and the presence of intermediate inputs.

[61] See Appendix B.3 for details.

[62] Safeway and Walmart report a share of intermediate inputs of approximately 25% (Stroebel and Vavra, 2019).

The second panel of Table 10 shows the validation exercise in which we use the model-generated data to estimate the response of prices to local shocks as in Equation (1). As α_1 becomes smaller, prices respond less to local conditions. Nevertheless, the coefficients estimated for the three calibrations are mostly in line with the data.

More importantly, the third panel shows the elasticity ratio, i.e., our main quantitative result. In the three calibrations the elasticity ratio is equal to about one-half. Hence, the value of α_1 is not important for the main result of the paper. Regardless of the share of intermediate inputs, prices are half as responsive to a regional shock than to an aggregate one. However, α_1 is important for the relative importance of uniform pricing vs. intermediate inputs. For larger values of α_1, local costs are more important and hence uniform pricing explains a larger share of the results. Based on this range of α_1, we find that uniform pricing explains between one-quarter and one-half of the price elasticity differences between regional and aggregate shocks.[63]

Table 10: Parameter Sensitivity: Local Labor Share in Sector $n = 1$

	α_1		
	Baseline	**Low**	**High**
Parameters			
α_1	0.41	0.25	0.66
Ψ (re-estimated)	1.32	1.34	1.29
Validation: Emp. growth x local share coefficient			
Without Time FE	0.38	0.23	0.64
With Time FE	0.43	0.26	0.74
Price index: elasticity ratio			
Uniform pricing	0.50	0.49	0.51
Uniform pricing + fixed int. inputs	0.83	0.88	0.76
Flexible pricing + fixed int. inputs	1.00	1.00	1.00

Notes: This table shows the results sensitivity when the share of local labor in sector $n = 1$ (α_1) is adjusted, re-estimating the disutility of work (Ψ). The middle panel shows the validation analysis based on equation (1) as shown in Table B1. The bottom panel shows the elasticity ratios as shown in Table 7.

We also study the sensitivity of our quantitative results to alternative estimations of the other parameters in Appendix B.4. We find that our main results are robust to changes around our baseline estimation.

Menu cost: There are many potential reasons for uniform pricing (i.e., operation costs, reputation costs, collusion incentives), which we cannot distinguish in our data. Thus, in the baseline model

[63]The share explained by uniform pricing is estimated to be $\frac{1-0.83}{1-0.5} = 34\%$ in the baseline, and $\frac{1-0.88}{1-0.49} = 24\%$ and $\frac{1-0.76}{1-0.51} = 49\%$ in the two alternative calibrations.

we imposed that firms in sector one have to set uniform prices. In Appendix B.5 we extend the model so that firms can choose between uniform or flexible pricing. There are two margins of regional heterogeneity, so, absent any adjustment cost, firms would prefer to set different prices across regions. First, there is ex-ante heterogeneity since regions have different preferences and sizes. To gauge the magnitude of the fixed cost, we consider a single firm that can adjust the price without any cost. The average firm's profits would only increase by 1.9%. Hence, the gains from setting flexible prices for each firm are small, and a fixed cost that amounts to 2% of profits would deter firms from setting different prices across regions.

Second, there is ex-post heterogeneity across regions due to regional shocks. It might be the case that after a regional shock, regions become more different and firms would like to set different prices across regions. As the size of the regional shock increases, regions become more different and there are more incentives to set different prices across regions. However, we find that for reasonable values of the regional shock, the fixed cost does not have to increase much to compensate for regional shocks. Even with shocks up to five times larger than in our benchmark model, the fixed cost has to increase by only 5% (i.e., to about 2.0% of profits) to justify why firms set uniform prices. Hence, ex-post heterogeneity does not add substantial additional gains for setting different prices across regions.

Thus, while we cannot distinguish among the various potential reasons for uniform in our data, this extension shows that a model with small additional costs (whatever their source might be) for flexible pricing should lead to conclusions and quantitative results similar to those from our baseline model.

Alternative model: The baseline model in Section 4 has price changes due to variations in marginal costs. Our main conclusions also hold when prices change due to demand shocks that affect the demand elasticity (due to non-homothetic preferences and income shocks).[64] 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 price elasticities, and (iii) regional elasticities are more biased measures of aggregate ones when regions are smaller or firms' sales are more equally distributed across regions.

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

[64]See Online Appendix D.

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 and sectors with multi-region firms and uniform pricing. We calibrate the model and show, as a validation, that the model is in line with 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 are sticky to regional shocks but more responsive to aggregate conditions. The estimated model predicts a one-half 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.

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Appendix

A Data

A.1 Uniform Pricing with Discount Prices

The paper documents two main empirical facts using list prices. This appendix shows that both results also hold if we take temporary discounts into account. An advantage of the data is that we can easily identify discount prices without relying on any *sales filter*. We observe up to three different prices for the same store and product. First, we always observe the list price. Second, we sometimes observe discounts, labeled as sale I, and/or sale II. The top panel of Table A1 shows that we have about 5% of observations with sale I, with an average discount of about 25%, and about 18% with sale II, with an average discount of about 15%.

The second and third panel of Table A1 show that there is uniform pricing even if we take sales into account. Once we have multiple prices we have to take a stand on what is the price paid by consumers. We consider four alternative definitions based on the minimum price between the list and/or sale prices, and show that in all of them prices are uniform across stores of the same chain.

Our second empirical finding is also robust to using sale prices. Table A2 shows that prices tend to react relatively little to local conditions, particularly so for firms that operate in multiple regions. We show here only the results with our broadest definition of sales, but it is robust to using the other two alternatives from Table A1. This result is consistent with the discount literature. For example, Kryvtsov and Vincent (2020) finds little evidence that sales co-vary with unemployment across U.K. regions, a finding that they attribute to uniform pricing strategies by large retailers (even though they are not able to observe prices at multiple stores of the same chain). Our results, which do rely on direct observation of sale prices at all stores, confirm their intuition.

A.2 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 component α_g, a chain component β_c, a chain-product component $\gamma_{g,c}$, and a residual $\epsilon_{g,s,c}$. The

Table A1: Uniform Pricing Including Sales

	Mean	Standard deviation	P25	P50	P75
Chain characteristics					
Number of Stores	113.4	181.4	10.5	27.5	116.6
Products with sale I (%)	4.6	5.4	0.0	2.5	7.7
Size sale I (%)	25.7	11.4	14.2	28.4	34.2
Products with sale II (%)	18.8	29.9	0.0	0.1	34.4
Size sale II (%)	14.7	8.2	9.2	13.9	17.9
Unique prices by chain					
List price	3.9	5.0	1.0	1.2	4.6
Min(list, sale I)	4.0	5.1	1.0	1.2	4.6
Min(list, sale II)	4.1	5.4	1.0	1.2	4.6
Min(list, sale I, sale II)	4.1	5.5	1.0	1.2	4.6
Unique prices by chain-type					
List price	2.5	2.1	1.0	1.2	4.0
Min(list, sale I)	2.6	2.2	1.0	1.2	4.2
Min(list, sale II)	2.6	2.1	1.0	1.2	4.1
Min(list, sale I, sale II)	2.6	2.2	1.0	1.2	4.2

Notes: The database has up to three reported prices. All products have a list price, while a subgroup also include up to two sale prices (i.e., sale I, and/or sale II).

Table A2: Regional Shocks and Store Prices Including Sales

	(1) All	(2) Local share < Median	(3) Local share > Median	(4) All	(5) All
Emp. growth $\left(\Delta e_{prov(s),t}\right)$	-0.0410	-0.186***	0.715***	-0.226***	-0.258***
	(0.0769)	(0.0707)	(0.227)	(0.0781)	(0.0835)
Local share $\left(local_{s,t}\right)$				-0.218	-0.192
				(0.217)	(0.186)
Emp. growth × Local share				1.066***	0.923***
				(0.271)	(0.250)
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. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. We define the price as the minimum between the list and sales I and II.*

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 $\mathbb{E}\left[\beta_c\right] = 0$, 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).[65] 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:

$$\hat{\alpha}_g = \frac{1}{N_g}\sum_{s,c} p_{g,s,c}, \qquad \hat{\beta}_c = \frac{1}{N_c}\sum_{g,s}\left(p_{g,s,c} - \hat{\alpha}_g\right),$$

$$\hat{\gamma}_{g,c} = \frac{1}{N_{g,c}}\sum_{s}\left(p_{g,s,c} - \hat{\alpha}_g - \hat{\beta}_c\right), \qquad \hat{\epsilon}_{g,s,c} = p_{g,s,c} - \hat{\alpha}_g - \hat{\beta}_c - \hat{\gamma}_{g,c},$$

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:

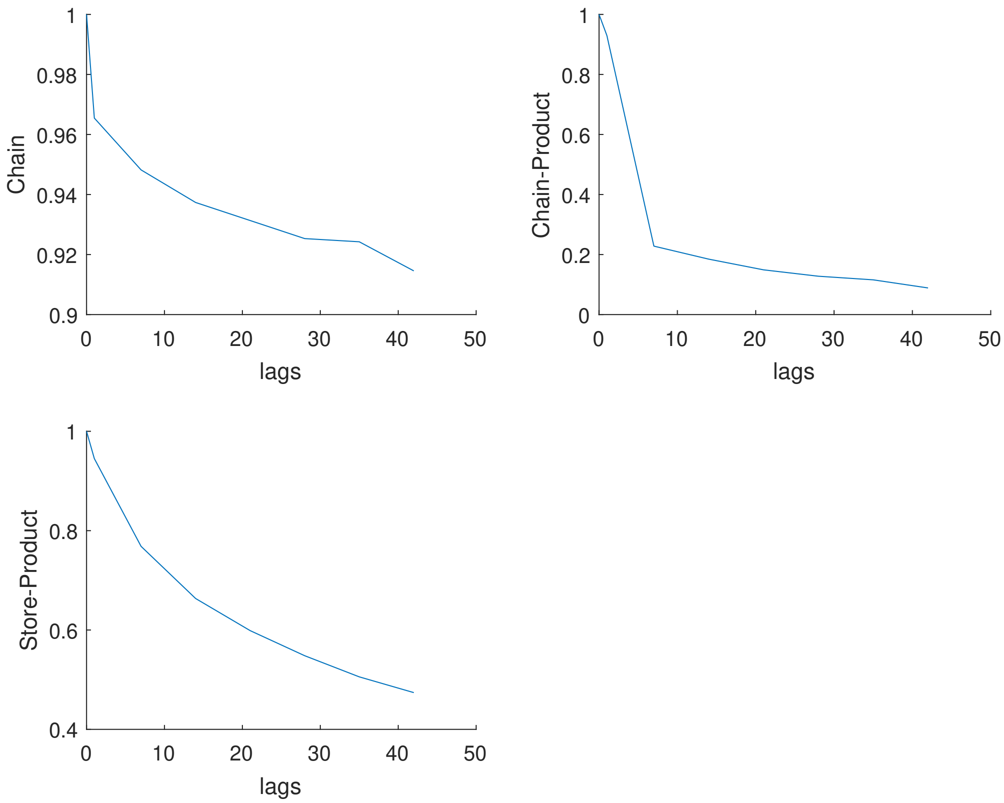
$$\text{Var}\left(p_{g,s,c} - \hat{\alpha}_g\right) = \text{Var}\left(\hat{\beta}_c\right) + \text{Var}\left(\hat{\gamma}_{g,c}\right) + \text{Var}\left(\hat{\epsilon}_{g,s,c}\right).$$

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 A1 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.

Alternative Decomposition The left panel of Table A3 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 explains 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

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

Figure A1: Price Dispersion Persistence



19% of that variance, while the other 19% corresponds to different prices in stores of the same province. Finally, the right panel of Table A3 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 A3: 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-province			19
Chain-good-province-store			19
Total	100	100	100

Stores

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

Notes: Left panel shows the roles of goods' categories and stores' provinces. Right panel shows the role of stores versus chains.

B Quantitative Results

B.1 Validation Regressions

Table B1 shows that the validation regressions using the model-generated data do a good job in replicating the empirical results, particularly the interaction term between employment growth and the local share.

Table B1: Validation

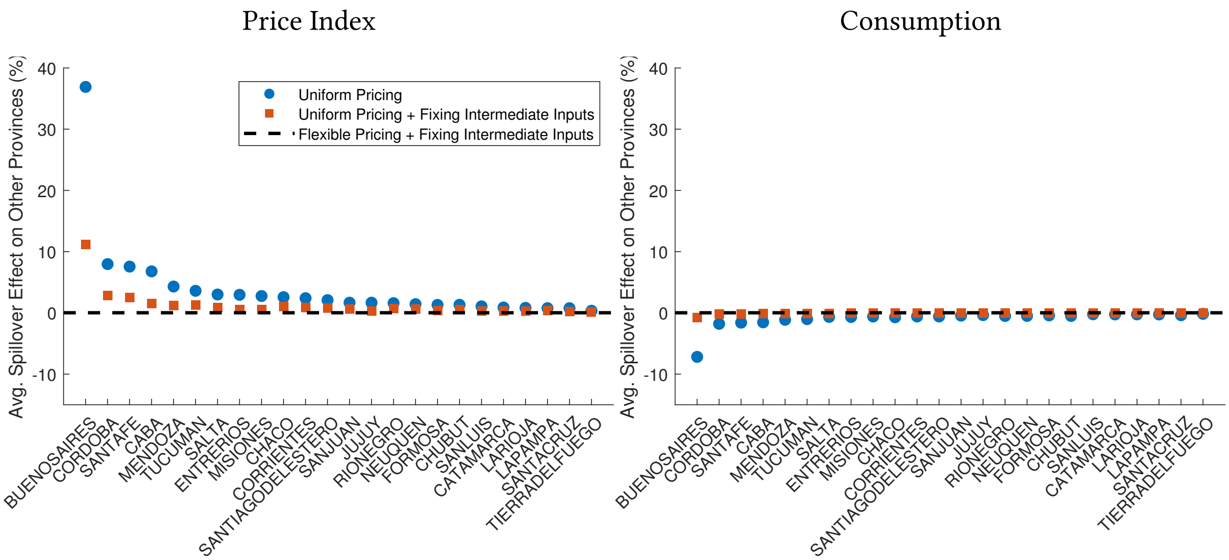
	Without Time FE		With Time FE	
	Data	Model	Data	Model
Emp. Growth	-0.137	-0.037	-0.174	-0.025
	(0.0569)	(0.0054)	(0.0582)	(0.0055)
Local Share	-0.269	-0.000	-0.237	-0.000
	(0.1890)	(0.0000)	(0.1440)	(0.0000)
Emp. Growth x Local Share	0.677	0.377	0.454	0.430
	(0.2160)	(0.0132)	(0.1990)	(0.0133)

Notes: We shock the simulated model 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. We then estimate (1) as in the data. In particular, we include store fixed effects as in Figure 4 and column 5 of Table 5. The table compares the estimates in the model to those in column 5 of Table 5.

B.2 Spillovers

Uniform pricing also implies that shocks in one region have spillover effects on other regions. As firms set the same price in all regions, 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 B1 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 B1: 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.

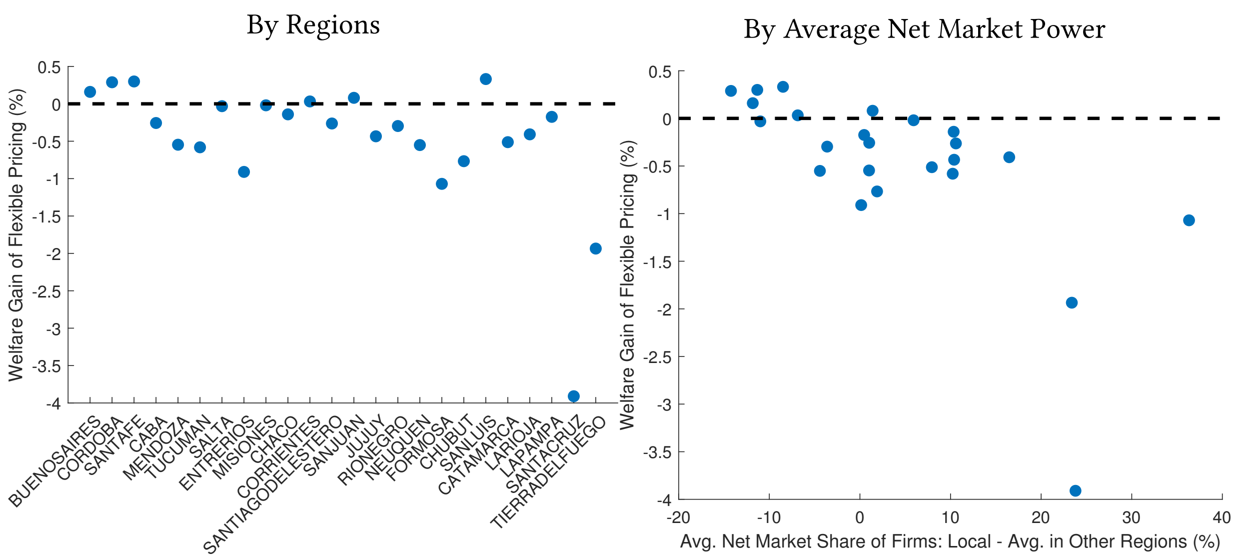
The average spillover effect on prices is 4.0%, while the one on consumption is -0.9% (always relative to the effect from an aggregate shock). But results are very heterogeneous depending on where the shock takes place. A shock in Buenos Aires, the largest region, leads to an average increase in prices of approximately 37% (relative to the aggregate shock) in the other regions. This then causes an average decrease in consumption of 7% (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 B1 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 are fixed to their baseline values), there are no spillover effects. To evaluate the importance of uniform pricing relative to intermediate inputs, Figure B1 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-fourth of the total price spillovers: the average price spillover effect is now 1.2% instead of 4.0%.[66]

B.3 Welfare Implications of Uniform Pricing

We evaluate the welfare implications of uniform pricing. We compute the consumption equivalent units of moving from uniform to flexible pricing for each region. The left panel of Figure B2 shows that households tend to lose when moving to flexible pricing (average loss of 0.5%), but welfare effects are highly heterogeneous, ranging from losses of 3.9% to gains of 0.3%.

Figure B2: Welfare Effects of Moving from Uniform to Flexible Pricing



Notes: The figure shows the welfare gains for each region of moving from uniform pricing to flexible pricing. The left panel plots the gains for each region, ordered by population size. The right panel shows the welfare gains according the average net market power that chains in sector one have in each region. The net market power of each chain-region is calculated as the market power of a chain in a region minus the average market power of such chain in other regions in which it operates.

A large driver of the heterogeneity of welfare effects has to do with the firms' heterogeneous

[66] 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.

market power. Households care about what prices would be if firms, instead of setting a uniform price, were able to set different prices in each region. In our model, equation 7 shows that firms set higher prices when they have higher market power. Thus, if firms have heterogeneous levels of market power across the regions, they would want to increase (decrease) prices in regions where they have more (less) market power. To capture this, we calculate the net market power of firm f in region r as the market power of firm f in region r (s^n_{rf} in the model) minus the average market power of such chain in other regions in which it operates,

$$\hat{s}^n_{rf} = s^n_{rf} - \frac{\sum_{r' \neq r, r' \in \Omega^n_{gf}} s^n_{r'f}}{\sum_{r' \neq r, r' \in \Omega^n_{gf}} 1}.$$

The average, within region, net market power is, therefore, a summary statistic that explains the direction in which prices would move. The right panel of Figure B2 shows, as expected, that regions where firms would have more market power under flexible pricing tend to prefer uniform pricing. For these regions, uniform pricing is a way of reducing prices. In line with Adams and Williams (2019), chains that operate in low-competition regions need to take into account that increasing prices may increase local profits, but would also lead to large profit losses in high-competition regions.

B.4 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 one-half of the aggregate elasticity. How sensitive is this quantitative result to alternative estimations? The left and middle panels of Figure B3 show the regional and aggregate elasticities when we increase each parameter by 1%, respectively.[67] While we find that most parameters lead to almost no changes, one set of parameters deserve mentioning. λ_1 and λ_2 measure the expenditure shares of sector one and two, respectively.[68] As we increase the expenditure share of goods that use intermediate inputs, there is a larger increase in the labor demand and wages, which increases the marginal cost. This generates similar increases in both regional and aggregate elasticities, implying that the difference between the two is almost unaffected.

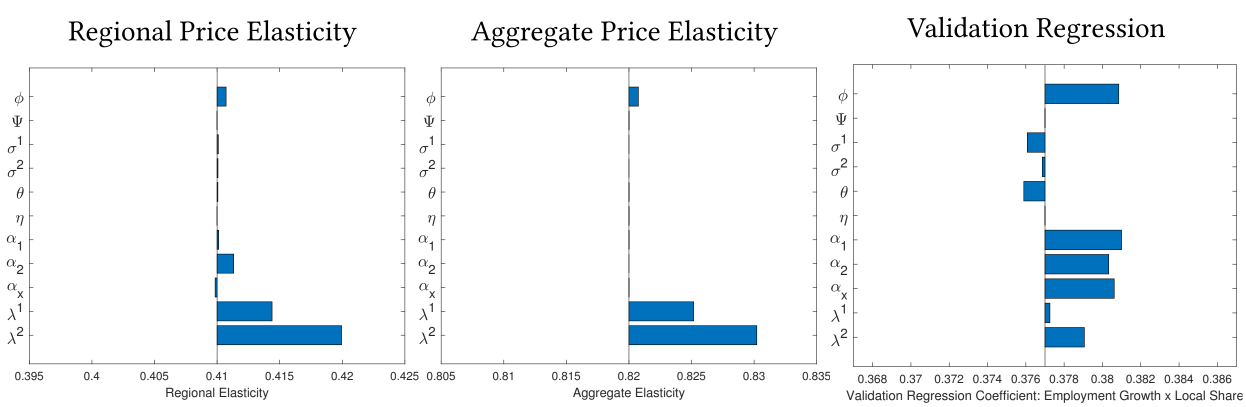
The right panel of Figure B3 shows, instead, how much parameters matter for the result that local

[67] 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 $\frac{\log(\text{Elasticity Ratio } |\Theta e^{\iota\epsilon}) - \log(\text{Elasticity Ratio } |\Theta e^{-\iota\epsilon})}{2\epsilon}$, 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%.

[68] Recall that $\lambda_3 = 1 - \lambda_1 - \lambda_2$. When we increase either λ_1 or λ_2 we are also decreasing λ_3.

firms react more to local shocks. In Section 5.1, we show that the model is in line with the data when estimating equation (1). Now, we show how much the coefficient from the effect on relative prices of the interaction between local shares and employment (β in equation 1) changes with the parameters. A few parameters deserve mentioning. First, the largest change takes place with the share of local labor . In particular, the higher α_1 (or α_2), 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. Second, the higher ϕ, the smaller the Frisch elasticity. When this happens, employment tends to increase less while wages (and, therefore, prices) tend to increase more. Thus, the regression coefficient β increases. Even though a formal analysis would require knowing the standard deviation of the parameters of interest, Figure B3 also shows that the regression coefficient β and, particularly, the elasticity ratio may be almost unaffected by sizable changes in most parameters.

Figure B3: Results Sensitivity to 1% Increase of Parameters



Notes: The figure shows the results sensitivity when each parameter is increased by 1% one by one. The left and middle panels show the regional and aggregate elasticities. The right panel shows the validation analysis based on equation (1) as shown in Table B1. The vertical lines reflect the elasticity ratio and regression coefficient, respectively, 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.

B.5 Menu-cost model

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. In this appendix we show that in a menu-cost model the returns to price discrimination for firms in are small. 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.

In the baseline model, we imposed that firms in sector one have to set uniform prices. We now study how large of a restriction this is. For this purpose, we extend the model so that firms can choose between uniform or flexible pricing $\pi^n_{gf} = \max\left\{\pi^{n,uni}_{gf}, \pi^{n,flex}_{gf}\right\}$. Under uniform pricing, the problem is as in the baseline model, i.e.,

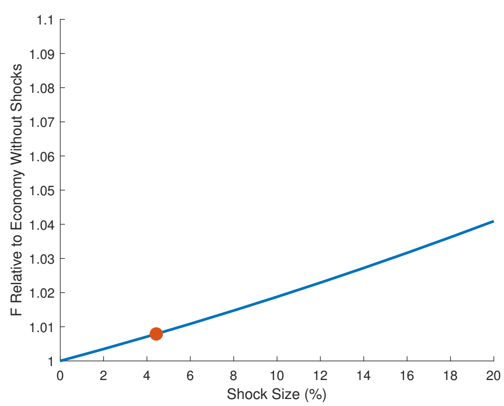
$$\pi^{n,uni}_{gf} = \max_{P^n_{gf}} \sum_{r\in\Omega^n_{gf}} C^n_{rgf}\left(P^n_{gf} - \delta^n_{rgf}\right).$$

We now assume, instead, that there is a per-region fixed cost F (in units of labor) to adjust regional prices such that profits under flexible pricing are

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

The main question is for what values of the fixed cost firms would prefer uniform to flexible prices across regions. There are two margins of regional heterogeneity. First, there is ex-ante heterogeneity since regions have different preferences and sizes. We find that with a relatively small fixed cost firms prefer uniform pricing. For example, with $F = 0$, profits would only increase 1.9% on average. Hence, the gains from setting flexible prices for the firms are small. A fixed cost that amounts to 2% of profits would deter firms from setting different prices across regions.[69]

Figure B4: Menu cost model



Notes: The figure shows the minimum F such that all firms prefer uniform pricing as a function of the size of the regional shock. The red dot shows the baseline value of shock sizes, which corresponds to one standard deviation of export commodities prices in the data.

[69] We can measure F in units of labor demand. Under the minimum F such that all firms set uniform prices, firms would have to increase their labor demand by about 4.9% to pay the fixed cost, on average.

There is also ex-post heterogeneity across regions due to regional shocks. It might be the case that after a regional shock, regions become more different and firms would like to set different prices across regions. As the size of the regional shock increases, regions become more different and there are more incentives to set different prices across regions. However, we find that for reasonable values of the regional shock, F does not have to increase much to compensate for regional shocks. Figure B4 shows how much the fixed cost would have to increase relative to the steady state as a function of the size of the regional shocks. Even with shocks up to five times larger than in our benchmark model, F only has to increase by less than 5% to justify why firms set uniform prices. Hence, ex-post heterogeneity does not add substantial additional gains for setting different prices across regions.

Online Appendix

This material is for a separate, online appendix and not intended to be printed with the paper.

C Data Appendix

C.1 Website Example

The left panel of Figure C1 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.

The right panel of Figure C1 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).[70]

C.2 Data Validation

The data are 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 leads us to believe that the self-reported prices are the real ones and that there are no mistakes in the database.

C.3 Uniform Pricing

Figure C2 shows the distribution of prices for several products, 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).

Table C1 shows that uniform pricing is a general characteristic of chains in CABA. For each day-product-store observation, we define the relative price as the log-price minus the mean log-price

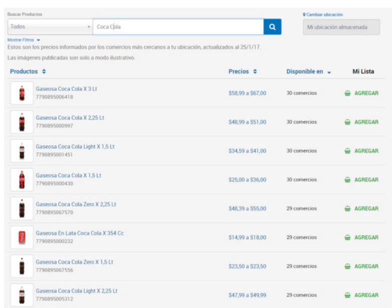
[70] Argentina has a population of approximately 44 million people. GBA and CABA account for approximately one-third and one-tenth of the country's population, respectively. The areas of GBA and CABA are 3,830 and 203 km^2, respectively. As a reference, CABA is about twice as large as Manhattan, both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

Figure C1: Precios Claros

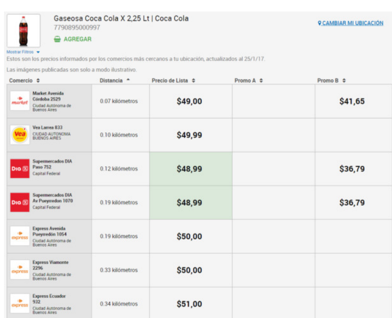
(a) Website

Step 1: Introduce Location

Step 2: Search for Product

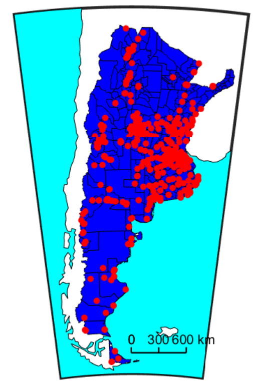


Step 3: Select Product

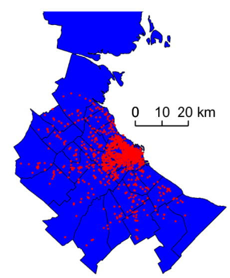


(b) Store Locations

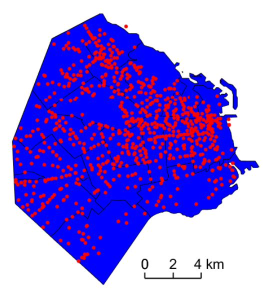
Argentina



Greater Buenos Aires (GBA)



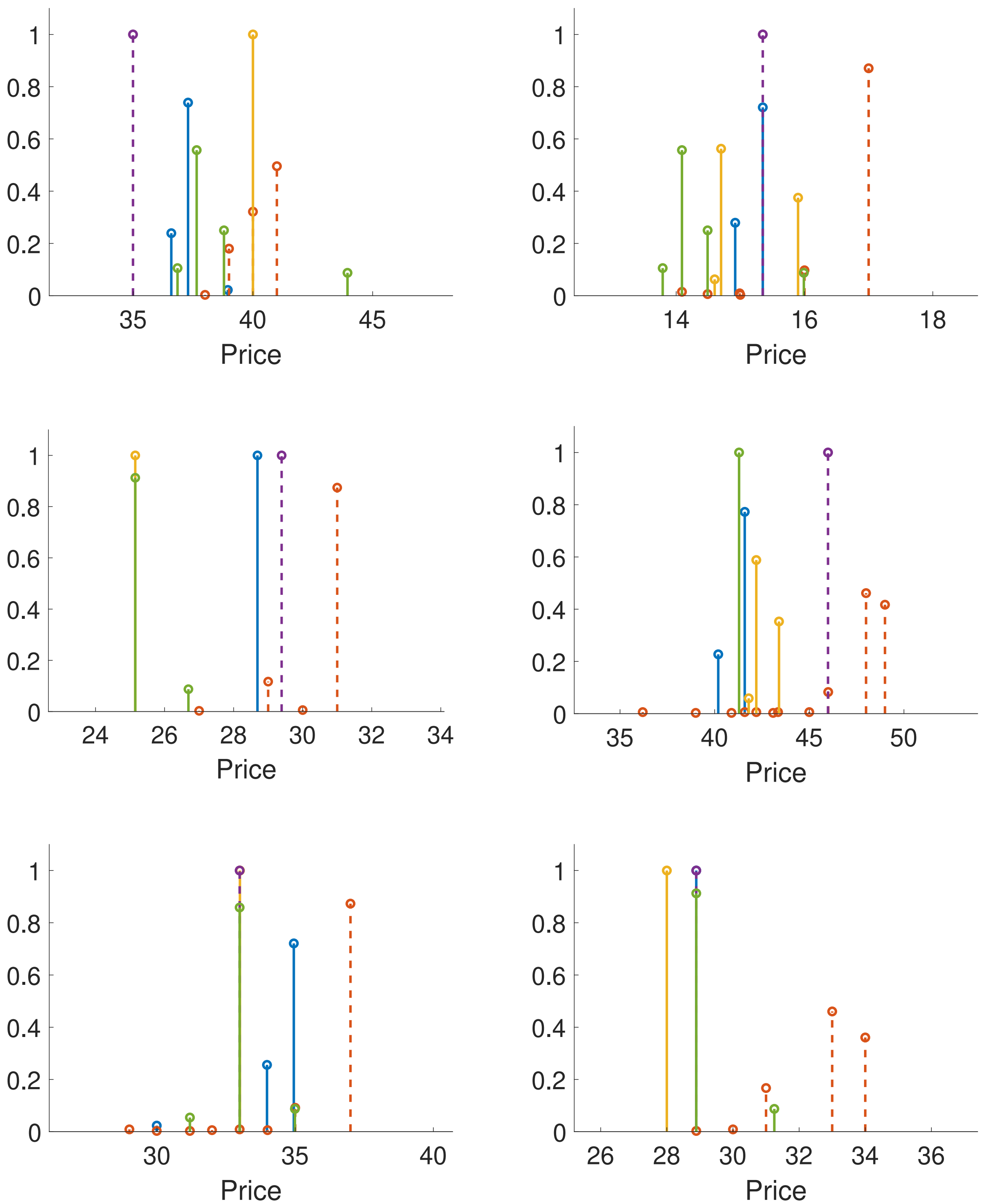
Buenos Aires City (CABA)



Notes: The left panel shows 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. The right panel shows the location of the stores, with each dot referring to a store in the given region.

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

Figure C2: Examples of Uniform Pricing



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

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.

Table C1: 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 relative (i.e., log-standardized) prices. This measure is explained in detail in the main text.

The last panel of Table C1 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 C2 repeats the analysis of Table C1, but for all national chains, and shows that uniform pricing is a general characteristic of chains in Argentina.

C.4 Price Change Synchronization

Table C3 shows that price-change coordination at the chain level also holds when looking at weekly or biweekly data.

Table C2: 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 relative (i.e., log-standardized) prices. This measure is explained in detail in the main text.

Table C3: 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% of other stores of any chain.

C.5 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).[71] More importantly, we are able to obtain information on the education, employment, and home characteristics of the people living in those areas.

Table C4 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 price 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 again, becomes insignificant once we control for the number of types of stores and number of provinces in which a chain operates.

The left panel of Figure C3 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.

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

Table C4: Uniform Pricing and Chain Characteristics

VARIABLES	(1)	(2)	(3)	(4)	(5)
Log(Numb of Stores)	0.477***	0.0812			0.151
	(0.0843)	(0.120)			(0.165)
Log(Numb of Provinces)		0.660***			0.691***
		(0.170)			(0.181)
Var(Log(education) within chain)			57.47***		-13.99
			(15.17)		(17.62)
Var(Log(distance) within chain)				0.584***	-0.0180
				(0.181)	(0.160)
Observations	20	20	20	20	20
R-squared	0.640	0.810	0.444	0.366	0.817

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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

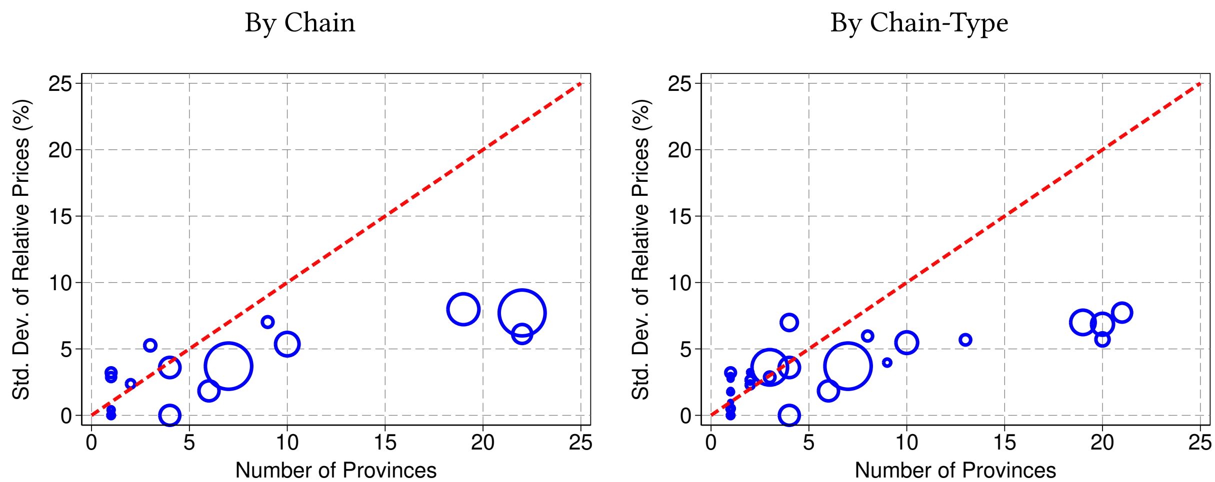
The right panel of Figure C3 plots the same relation but defines chains in a stricter way, i.e., according to chain-types. In this case, the relation between uniform pricing and the number of provinces is even weaker, suggesting that chains may use subdivisions within the chain to partially discriminate prices. Once that is done, price differentiation between locations is not as strong.[72]

C.6 Effects of Regional Shocks: Role of Buenos Aires

In Section 3.2, we showed that prices tend to react relatively little to local conditions (based on employment data at the province level), particularly so for chains that operate in multiple regions. In particular, 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 conditions. Given that almost 40% of Argentineans live in Buenos Aires province and 29% of the stores are in Buenos Aires, we want to confirm that our results are not driven exclusively by Buenos Aires. For this, we extend our regression equation (1) to allow for the share of the

[72]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 C5 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.

Figure C3: 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 C5: 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

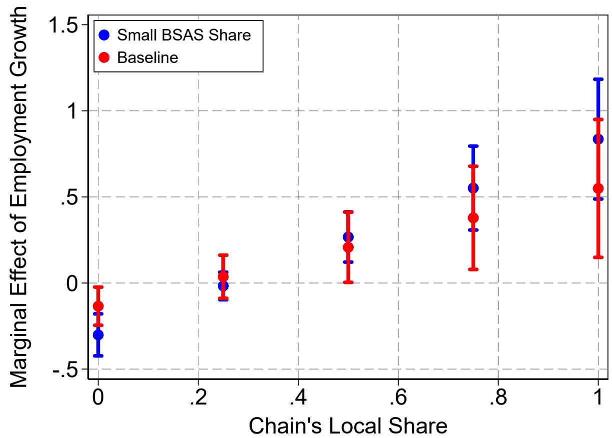
Notes: We compute the variance of the log of alternative characteristics for locations in which a chain operates relative to the unconditional variance. This table reports the average and standard deviations of these measures across chains.

chain's stores that are in Buenos Aires, $bsas_{c(s),t}$, to have an effect:

$$\begin{aligned}\Delta p_{s,t} =& \alpha_s + \gamma_t + \beta_1\ local_{s,t} + \beta_2 \Delta e_{prov(s),t} + \beta_3 local_{s,t}\ \times\ \Delta e_{prov(s),t} + \\ &+ \beta_4\ local_{s,t} \times bsas_{c(s),t} + \beta_5\ \Delta e_{prov(s),t} \times bsas_{c(s),t} + \\ &+ \beta_6\ local_{s,t} \times \Delta e_{prov(s),t} \times bsas_{c(s),t} + \epsilon_{s,t}.\end{aligned} \tag{10}$$

In addition to the baseline results from 4, Figure C4 plots the marginal effect of employment growth $\Delta e_{prov(s),t}$ on store price growth $\Delta p_{s,t}$ for chains with low participation in Buenos Aires, i.e., at the 10th percentile ($bsas_{c(s),t} = 0.12$). We do not find any statistically significant differences between the baseline results and the ones focused on chains with low participation in Buenos Aires. Thus, the results are valid for the whole country and not only for Buenos Aires.

Figure C4: 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. The baseline results are those from Figure 4, while the alternative is based on the estimates from equation (10) evaluating the Buenos Aires share, $bsas_{c(s),t}$ at its 10th percentile (i.e., 0.12). The vertical lines refer to the 95% confidence intervals.

C.7 Effects of Regional Shocks: An IV approach

Our main evidence regarding the differential effect of regional shocks on stores with different local shares is not to be interpreted as causal. Our model in Section 4 is useful to overcome this limitation since we use the model to generate and properly evaluate the causal effects of exogenous regional and aggregate shocks—estimating the same regression and showing that it is in line with this empirical findings. As an alternative approach, we also evaluate here an instrumental variable approach akin to Guren, McKay, Nakamura, and Steinsson (2021)—though ours is more limited since we do not have as much regional information as they do. In particular, we estimate the elasticity of our local employment variable (i.e., at the province level) to supra-provincial employment:

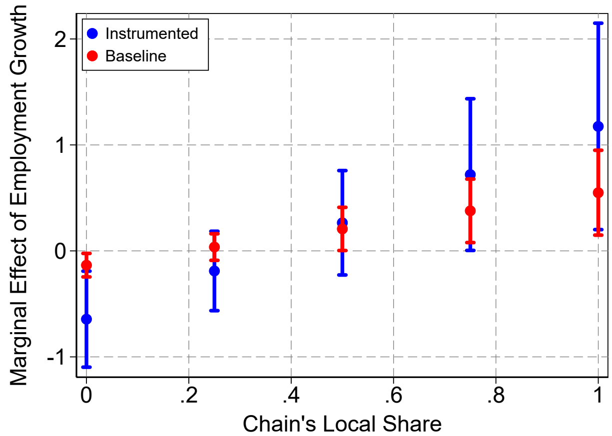
$$\Delta e_{prov,z,t} = \alpha_{prov} + \beta_{prov}\Delta E_{z,t} + \delta_{prov}\Delta\tilde{E}_t + \varepsilon_{prov,z,t}, \tag{11}$$

where $\Delta e_{prov,z,t}$ is the growth rate of employment in province $prov$ (which is in zone z) in period t, $\Delta E_{z,t}$ is the growth rate of employment in zone z in period t, and $\Delta\tilde{E}_t$ is the country-wide growth rate of employment in period t. Thus, as in Guren, McKay, Nakamura, and Steinsson (2021), coefficients β_{prov} and δ_{prov} may be interpreted as capturing the province-specific sensitivity to employment variation at the zone and national level.[73] Thus, after estimating equation (11), we use $x_{prov,z,t} = \hat{\beta}_{prov}\Delta E_{z,t} + \hat{\delta}_{prov}\Delta\tilde{E}_t$ as an instrument for $\Delta e_{prov,z,t}$. Figure C5 shows the main result of interest for our purpose based on this approach, as well as our baseline result from Column

[73]We follow the standard geographical definition of regions in Argentina, which splits all provinces into 6 zones.

(4) in Table 5. While the instrumental approach is noisier, our baseline results lie within the 95% confidence interval of the instrumented results. Thus, this evidence suggests that our result that prices in stores with larger local shares covary more with local conditions is robust to introducing sources of plausibly exogenous variation.

Figure C5: Marginal Effect of Regional Shocks on Store Prices: An IV Approach



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 5 as well as our instrumental variable approach based on Guren, McKay, Nakamura, and Steinsson (2021). The vertical lines refer to the 95% confidence intervals.

D Alternative Model

The baseline model in Section 4 has price changes due to variations on marginal costs. Our main conclusions also hold when prices change due to demand shocks that affect 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 price elasticities, and (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.[74]

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.

D.1 Households

There is a representative consumer in each city with period utility

$$u_{j,t} = \int_{\omega \in \Omega_{j,t}} s_j(\omega) \log\left(q_{j,t}(\omega) + \bar{q}_j\right) d\omega, \tag{12}$$

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 3, which show that prices change with income shocks.[75] 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

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

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

$$q_{j,t}(\omega) = \max\left\{0, \frac{s_j(\omega)}{\bar{S}_{j,t}} \frac{y_{j,t} + P_{j,t}\bar{q}_j}{p_{j,t}(\omega)} - \bar{q}_j\right\}, \tag{13}$$

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

[74] 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).

[75] 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.

positive demand for all varieties.

D.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.

D.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 (13) as given. The solution is

$$p_{j,t}(\omega) = \left[c_{j,t} \frac{s_j(\omega)}{\bar{S}_{j,t}} \left(\frac{y_{j,t}}{\bar{q}_j} + P_{j,t}\right)\right]^{1/2}. \tag{14}$$

Given the demand function (13) and pricing (14), 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 $s_j(\omega) \geq \underline{s}_{j,t}$.[76] The threshold is defined as the taste such that consumption is equal to zero; that is,

$$\underline{s}_{j,t} \equiv \frac{\overline{S}_{j,t}\overline{q}_j c_{j,t}}{w_{j,t} + P_{j,t}\overline{q}_j}. \tag{15}$$

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 $\overline{\omega}_t = s_2\left(\underline{s}_{2,t}\right)^{-1}$.

D.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

[76] To see this, replace the equilibrium price (14) on the demand function (13) and note that it is increasing in $s_j(\omega)$.

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 (13) as given. The solution is

$$p_t(\omega) = \left[\sum_{j=1}^{2} \frac{M_j}{M_1 + M_2} c_{j,t} \frac{s_j(\omega)}{\bar{S}_{j,t}} \left(\frac{y_{j,t}}{\bar{q}_j} + P_{j,t}\right)\right]^{1/2}. \tag{16}$$

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

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

D.3 Quantitative Exploration

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

D.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 D.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 $\Omega_1 = \left[\underline{\omega}, 1\right]$ out of which varieties $[\overline{\omega}, 1]$ are sold only in City 1. Hence, we target this moment as $(1 - \overline{\omega}) / \left(1 - \underline{\omega}\right) = 0.07$.

Section 3.2 shows that prices of firms with a lower local share react less to regional shocks. In the model we define the local share as $local\,(\omega) = M_1 q_1\,(\omega) / (M_1 q_1\,(\omega) + M_2 q_2\,(\omega))$.[77] 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 D1 shows the estimated parameters and target moments.

Table D1: 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

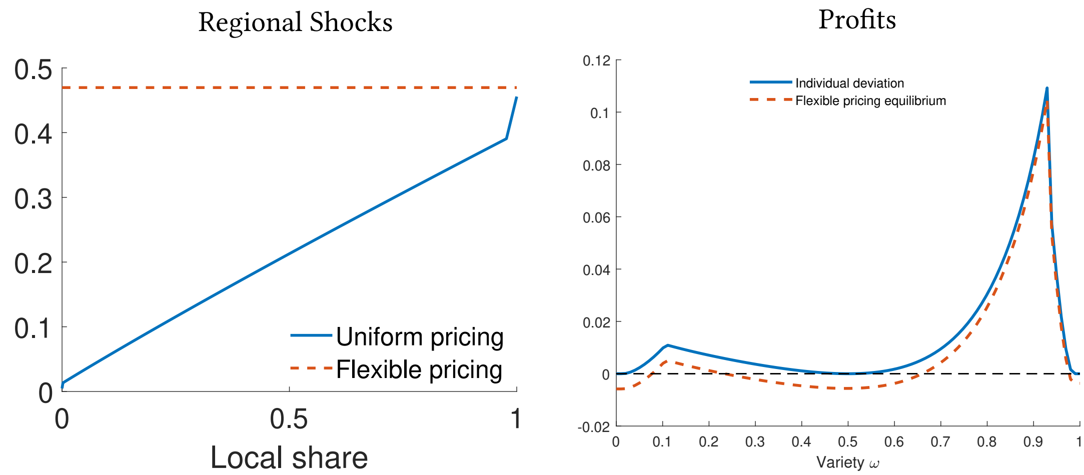
Notes: The data of price responses and local shares are based on the estimates of Section 3.2.

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 D1 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 4, while those in the flexible-pricing model do not.

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 D1 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

[77] 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 D1: Uniform vs Flexible Pricing



Notes: The left panel 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 right panel shows the change in profits when the economy moves from uniform to flexible pricing.

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%.

D.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 $P_{j,t}^{index}$. We define the elasticities as

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

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 D2 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 D2 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 D2: 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.

D.5 Alternative City Configurations

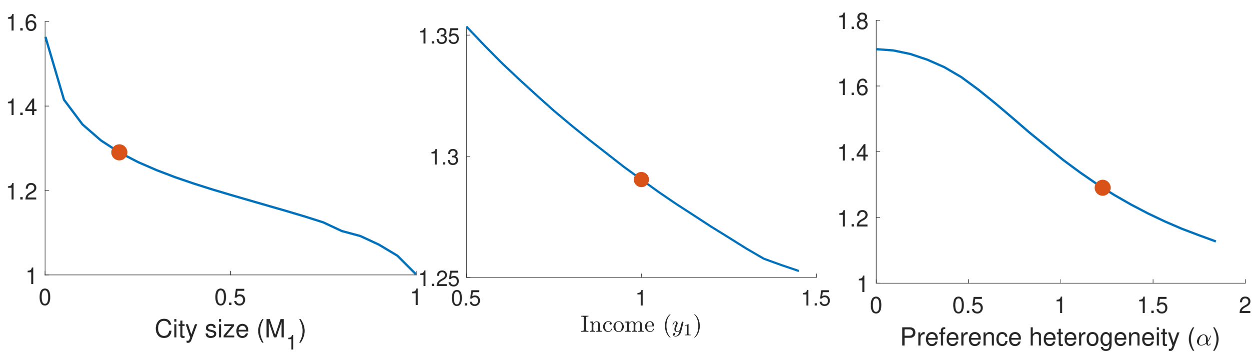
We consider alternative setups to study the quantitative importance of each assumption. We evaluate the effects of city sizes, income, and preferences. We find that the amplification of the response of consumption to regional relative to aggregate shocks is robust to all the alternative specifications.

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 D2 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 that 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 D2: Alternative City Configurations



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