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Retailer Markup and Exchange Rate Pass-Through: Evidence from the Mexican CPI Micro Data

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Abstract

I develop a structural model with nested CES preferences to obtain optimal markups for heterogeneous retailers when the prices of all their inputs are exogenous. The model predicts that, if the taste parameters are constant over time, the markups for retailers with higher market share are higher but have more flexibility, implying an incomplete pass-through of retailer input price into final retailer prices. I then focus on the exchange rate pass-through (ERPT) and use a unique data set of all the price changes of tradeable merchandise in the Mexican Consumer Price Index (CPI) data by store type to test the model. I find, consistent with the model, that (1) ERPT is different by store type; and (2) products sold in stores with negligible market share have the same ERPT regardless of the store type. Both results imply that the ERPT is estimated with bias when the store information is not used.

Keywords: Exchange Rate Pass-Through, Markups, Retailers

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1 Introduction

The most prominent micro-data papers that study exchange rate pass-through (ERPT) assume it is completely exogenous from the point of view of the final retailer and, under certain conditions, it can even be optimally decided by the producer, depending on its market share.[1] Those papers use new micro-founded structural macroeconomic models because using the old models the ERPT should be close to 1 while empirically it is not.[2] For identification purposes, the new models rely on the assumption that, once the products leave the factory for the retailer who will sell to the final consumer (perhaps even in another country), the value-added chain going all the way to final consumption (transportation, refrigeration, marketing, etc.) is perfectly competitive.[3]

In this paper I develop a simple model with nested CES preferences where I relax the assumption that retailers (the last link of the distributor value-chain), who sell multiple products from different producers, are perfectly competitive and assess the implications of this result for the input price elasticities, especially the ERPT. I find the implications of relaxing this assumption to be large and important, from all theoretical, methodological, empirical and policy-relevant perspectives. The implications can be summarized with the following two statements: 1) if the store information is not used, then the point coefficient of the measured ERPT in a regression does not converge to the true ERPT but to the ERPT plus a correction term that is proportional to the market concentration of the retailers; and 2) only for the case that not a single store has market power then the point coefficient of the measured ERPT in a regression converges to the ERPT, and this coefficient should not vary by store type.[4] All prominent micro-data papers until now have assumed that the retailers have no market power, thus jumping directly to (2) without checking whether (1) is relevant either in the data or in a

[1] The ERPT measures the elasticity of local prices with respect to the exchange rate. Throughout the paper, local prices will be in Mexican pesos and the exchange rate will be the MXN/USD exchange rate.

[2] See Goldberg and Campa (2010) for a study on 21 industrialized economies' ERPT into the CPI.

[3] See Burstein and Gopinath (2014) for an extensive literature review. In this context, a value-added chain is perfectly competitive if all the firms that add value to the product once it leaves the factory are price-takers when buying and re-selling the product.

[4] The term "measured ERPT" designates the coefficient of regressing the log-change in price against the log-change in exchange rate and other controls. See section 5 for the complete list of controls.

model. It turns out that it is.

I had access to the 23 million observations the Mexican CPI micro-data set from INEGI, with the retailer names and their INEGI-generated store types.[5] It is easily verifiable that not only do the same products in the same city have different retail price levels depending on the store type where they are sold, but also that the measured ERPT differs by store type (see table 5 in the Appendix).[6] I find that in Mexico the price volatility varies by store type for the same goods in the same city. In particular, the data show that, for the entire data set, between June 2009 and June 2018, the prices of the same generic tradeable goods in Mexican convenience stores were on average twice as volatile as the prices in Mexican supermarkets.[7] In the same time period, public markets are 1.6 times more volatile than supermarkets, while department stores are 0.9 times as volatile. If all the stores in the same city face the same exchange rate dynamics, this suggests that one possible explanation on why the measured ERPT in Mexico is heterogeneous by store type is the difference in price volatility. This implies that at least one assumption in the standard model has to be modified in order to match this variation as observed in the data.

For this paper, I relax the assumption that markets are perfectly competitive at the retail level in an otherwise standard model of retailer price setting to isolate one possible source of the heterogeneous measured ERPT.[8] I found that, by relaxing this assumption, the retailers not only choose their markups, but they endogenously produce store-specific levels of measured ERPT: a common ERPT for all the stores that comes directly from the exchange rate move-

[5] INEGI is the acronym of Instituto Nacional de Estadística y Geografía, the public institution in charge of statistical data in Mexico. One of their tasks is to measure and publish the official inflation data for Mexico.

[6] In order to get long time series of price data from the same stores, six INEGI-generated categories were used for estimation: convenience store, supermarket, public market, department store, price clubs and specialized store. Tianguis and subsystems were eliminated as explained in section 4. Price club data are used but not reported due to confidentiality. Public markets is the name given in Mexico to what can be described as malls of semi-informal grocery stores.

[7] Details on which products constitute tradeable merchandise for the purposes of this paper are in section 4. Generic products in Mexico are similar to the Eurostat's COICOP varieties. There are more than 240 generic products in Mexico's CPI, while there are more than 10,000 different products in the data base. The generic category of products (i.e. beer) will be the unit that describes products in order to be able to make comparisons across cities and over time.

[8] See Francois and Manchin (2019) where the pricing decisions of distributors and in general the transportation industry are studied to explain heterogeneous rates of ERPT, taking the final retailer as competitive.

ment, minus an indirect store-specific markup flexibility coefficient that is proportional to the market share.[9] One of the implications of the model is that store types with a large market share have less price volatility due to the markup flexibility component, which seems consistent with the data. I propose an econometric correction that isolates the common ERPT for all the stores and a store type-specific markup flexibility which, up until now, was not separated in the micro-data literature. The implication of this econometric correction is that the measured ERPT is the common ERPT plus the average store type-specific markup flexibility component (a negative number) so the measured ERPT is downward biased if it does not take into account the store market share.

I derive two main predictions in the model: (a) individually estimated, stores with a large market share will have the lowest measured ERPT and (b) products sold in stores with an infinitesimal market share in the same city will have the same measured ERPT, no matter what type of store. The last prediction implies that the previous literature on ERPT with micro-data and structural models is a particular case of this setting: the case where there are no stores with market power in any city. This last prediction is not surprising, given that this is the exact assumption that was relaxed in this model, but the policy and econometric implications are important: if it holds, then we have been estimating ERPT with bias. More generally, my model suggests that all the retail price elasticities with respect to input prices are estimated with bias in just about every country, meaning that we have unreliable estimates for other relevant policy parameters in other areas of the literature, such as the VAT pass-through into prices. I test the model with the data and the results suggest that both of these predictions hold. To the best of my knowledge, this is both the first time any published research has used store information with Mexican CPI data or tried to explain ERPT due to the retailers using CPI micro-data in any country.

The contribution of the paper to the research literature is multi-dimensional. First, the theoretical contribution is that the optimal markup of a retailer with some market power is endogenously flexible, which means that the measured ERPT varies with the local retailer

[9]It is an indirect effect because the markups change by changing the prices of the store relative to the competitors, who changed their prices due to changes in the exchange rate.

characteristics (which can depend on the local market characteristics) and not only with the product characteristics or the geographic location of the final retailer. All previous results in the literature that focuses on ERPT with micro-data can be collapsed to the case where no retailer in any city has any market power. The empirical contribution is that I had access to a very detailed micro-data set and the data suggests that inflexible markups in retail are an implausible assumption for Mexico. This implies from the model that measured ERPT and other input price elasticities have been estimated with bias not only in Mexico, but potentially everywhere where micro-data has been used to estimate this parameter. The methodological contribution relies on the fact that CPI data sets all over the world most likely have store characteristics, so I propose an econometric correction for the estimation that uses store data as the key ingredient for identification and unbiased estimation. Finally, the policy contribution is that policymakers such as central banks, with the same data sets that have been used up until now, can correct both their future estimates and also their old estimates of important elasticities in the economy, one of them being the ERPT. This correction does not necessarily need to be public information (due to the confidentiality of the data) but it can certainly be done internally with a view to making better decisions on monetary policy.

The aim of this paper is to fit and enrich two rapidly growing areas of research in the literature. The first area is the one that focuses on flexible markups by taking the producer prices as exogenous and adding the dimension that retailers have flexible markups. This paper shows that the market share of the retailer is an important determinant of the markup level, but also of the markup flexibility. In fact, a non-negligible market share in retail implies that the markups are flexible and thus makes most models untestable if the price data are collected from any large retailer. The second area in the literature that this paper points at is the one that studies ERPT, where the consensus is that it is small. I build a model with a closed form solution where one of the implications is that, if every retailer is zero-measure, then the estimating equations collapse to the ERPT estimations used in almost all of the literature, and that if retailers are non-zero-measure then there is a correction term that biases the estimates of the elasticities of the input prices on final prices, acting as an omitted variable bias. This means that the elasticity of the final price on exchange rates (ERPT) is most likely biased in everything written about ERPT with retail-level micro-data up until now.

The paper is organized as follows. Section 2 reviews the latest papers estimating ERPT with micro-data and locates the paper and its contribution in the literature. Section 3 sets up the model and shows that, if the preference parameters do not change over time, then the elasticity of the final goods price with respect to input prices (including the exchange rate) are biased. Section 4 lists and explains the data sets used for estimation and briefly describes how the spatial competition measures were built and section 5 shows the different estimations of the ERPT conditional and unconditional on retailer information. Finally section 6 summarizes the results and concludes.

2 Exchange Rate Pass-Through with micro-data

In the last 18 years, the CPI and the exchange rate in Mexico have changed in almost the exact percentage. The same can be said in the period where price micro data are available (starting mid 2009, ending mid 2018). As figure 1 shows, in the short run they have some (low) correlation. However, the time series fail cointegration tests. And while these tests seem naïve for a modern empirical paper, up until not so long ago the ERPT was studied as a macro "strong parameter" that only depended on the monetary policy regime or the exchange rate volatility and persistence, and where aggregate indices were sufficient for identification.

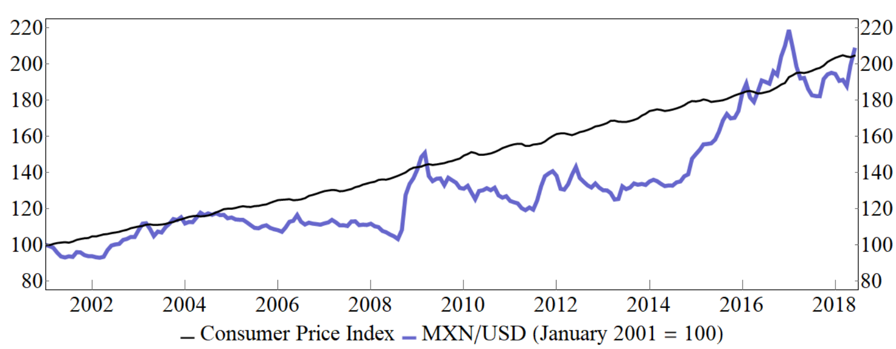


Figure 1: CPI and Exchange Rate in Mexico from January 2001 to June 2018.

But this has changed and now structural micro models assume that retailers have inflexible markups and are able to produce the incomplete ERPT we observe in the data. The empirical methods to test those models have led to computationally intensive work to obtain at-the-dock unit prices in order to study the ERPT as an endogenous elasticity.[10] Papers that combine at-the-dock unit prices with retailer prices either from scanner data, consumption surveys, or even the CPI micro-data have produced important contributions to our understanding of ERPT. Most importantly, the findings are summarized in the fact that there are many reasonable assumptions (an example of those being dropping the multiplicative iceberg costs) that lead to the ERPT not being theoretically equal to one but much lower, like in the data. Now we know that if the value-added chain after a product leaves the factory is perfectly competitive, then the ERPT depends on dollar denominated input prices, distance to the border (Burstein et al. (2003)), import content, strategic complementarities faced by the producer (Gopinath et al. (2010)), market share of the exporter (Amiti et al. (2014)) and similar structural, relatively constant features in the economy.

Recent literature has shown that unbiased estimates of the parameters of those models are obtained by assuming that, all at once, (a) the value-added chain in the country where the product will be consumed is all perfectly competitive, (b) the inputs added to the merchandise between the factory and the final retailer, such as transportation and refrigeration, are an exogenous input for the retailer and not part of the production function of the factory, and (c) the value-added inputs have a constant elasticity of substitution with the rest of the retailer inputs.[11] These three conditions imply, among other things, that the same products in the same city will have the same cost as long as retailers have the same technology and the same ability to obtain inputs like transportation, workers, the products of the factory, etc. at unique prices locally. Allowing for different productivity levels in technology then they will have different cost levels, but the same input to retail price elasticities such as the ERPT because the markup is inflexible and so all the variation of the price is explained with variations in the cost, which is a common shock.

[10] See Burstein et al. (2003), Casas et al. (2016), Auer et al. (2018).

[11] Additive iceberg costs such as the ones in Burstein et al. (2003) are one example with elasticity equal to 0.

In this paper, in the spirit of models such as the ones in Amiti et al. (2014) and Hottman et al. (2016), I develop a structural model with nested CES preferences to obtain optimal markups for heterogeneous multi-product retailers when the prices of all their inputs are exogenous but their market shares known. The model allows for non-zero measure retailers within their store type, and non-zero measure store types. The resulting equilibrium pricing rule features a variable markup of price over marginal cost that is common across all goods in the same store, and different across stores (an analogous result as in Atkeson and Burstein (2008), where multi-product producers have common markups). The model features that markups are high for retailers with high market share within their store type, and also high for stores within a store type with high expenditure share in the economy. Moreover, the model predicts that if the taste parameters are constant over time, then the higher markups are more flexible, with a negative coefficient. This means that the same percentage change in marginal costs implies a lower percentage change in final price in stores with high share (and high markup), but more importantly, that the low sensitivity of the retailer price to the exchange rate is a direct consequence of the larger market share and not a technological difference. Since the ERPT is the elasticity of the price with respect to changes in the exchange rate leaving everything else constant, this means that the ERPT is measured with a bias when there is no explicit adjustment on the markup level due to changes in the exchange rate. The resulting "usual" estimate of ERPT turns out to be a weighted average of the store-type-specific ERPT.

This evidence for Mexico can be linked with Cravino et al. (2018), where they find that in the United States, the prices of the goods consumed by high-income households are less volatile than those of the goods consumed by middle-income households. While my model has homothetic preferences and has nothing to say about the consumption bundles of rich and poor households, notice that in Mexico in 2010 only 7 percent of the households were located in high income neighborhoods but 20 percent of department stores and supermarkets (which exhibit low price volatility) were located in high income neighborhoods.[12] If Mexican people do their shopping close to home, then those results and the ones in this document are

[12]This information was obtained using store locations (geographic coordinates) from DENUE (2010) and from the Census of Population 2010 which also has geographic coordinates. Both data sets are from INEGI.

comparable.

This result of heterogeneous markups, which result in a wide distribution of prices of the same good, also contributes to the results found in DellaVigna and Gentzkow (2017), where the data for the United States shows that department stores, pharmacies and food stores impose (almost) uniform pricing across locations, and the authors even give an estimate of the potential gains of spatial pricing. This paper assumes that retailers set uniform markups by city, not uniform prices in the entire country, and at least in Mexico this seems to be the case.

Usually, nested CES models and other international economics papers give the producers of the goods all the pricing decision, and assume that once this decision is taken, retailers pass-through 100 percent of this decision onto consumers via an inflexible markup. For example, Gopinath and Itskhoki (2010), Amiti et al. (2014), Auer and Schoenle (2016), and many others have pricing-to-market decisions and strategic complementarity which then retailers just levy onto consumers. To the best of my knowledge this is the first time CPI data collected in retailers is used to study retailer markups, so there may be a lot of variation in prices that had always been neglected that I now exploit. The model predicts that there are two dimensions along which markups vary across stores.

First, they vary in levels. The markup is larger for retailers within a store type with large market share (i.e. retailers in the supermarket store type, no matter what the market share of the retailer within the supermarkets is), but can be larger or lower for retailers with a large market share within their store type (i.e. retailers with a large share in the supermarket store type, no matter what the share of supermarkets is overall) depending on whether retailer within store types are better substitutes than retailers across store types, or the other way around, respectively. The second dimension is in the elasticities of the markups. Higher markups are more flexible, and because they have negative partial derivative with respect to relative prices, the same variation in costs implies that the observed percentage change in price in the higher markup retailers is lower. Since retailers with large shares in their own type of store are the ones with the highest markups, this means that these retailers will have the most flexible markups. For the same increase in marginal costs in every store (for example, a generalized increase in the cost of beer), the model predicts that retailers with the largest market share will increase the price of the final good (cold beer), in percentage terms, the least.

3 Model Structure and Identification Strategy

Given the price data of the product-store over time, and given that it is not possible to know the producer's pricing decision from the CPI data, I model the local retailer's price setting decision taking the producer price as given. Furthermore, for identification purposes, I assume that producers do not incur in pricing-to-market strategies between or within cities in Mexico. This way I modify the common assumption in the literature of using CPI data assuming that all the markups are rigid once the product has been sold by the producer. The model is explicitly simple, and its main objective is to give closed form solutions of loglinearized expressions for the data generating process of price changes, without an explicit model for internationally strategic producer decisions. The model allows for an extensive family of seminal monopolistic competition, ricardian technology, or pricing-to-market models to be tested if, for example, producer price data was available. Also, if data on quantities purchased was available, then elasticities of substitution would be feasible to estimate too. The aim of this paper is not to deepen the estimation strategy of flexible markup models, but to highlight that ignoring the possibility of flexible markups can potentially lead to biases estimating the ERPT.

Preferences in the model are characterized by a nested CES demand structure with 3 nests, where the consumers in each location (indexed with ℓ, and in the data locations are cities) have preferences over a fixed set of store types (indexed with τ), and within types of stores, preferences over retailers (indexed with r), and within the retailers, they have preferences over generic products (indexed with g), which in the data will be tradeable merchandise goods.[13]

[13] See Kochen and Sámano (2016) for an extensive description of the selection of the "tradeable merchandise goods" bundle of the CPI. They are basically everything that is not a service, with minor exceptions. For example, hotels are included as tradeable goods.

Generic products are purchased by retailers, which are single-plant firms (i.e. make decisions in only one location where they have some market power), from producers for the same price all over Mexico, and then the retailers add value (transport the good from the factory/port to the location, refrigerate it, hire workers to sell it, etc.), and decide a price for the generic product in their store, where consumers go purchase the final goods.

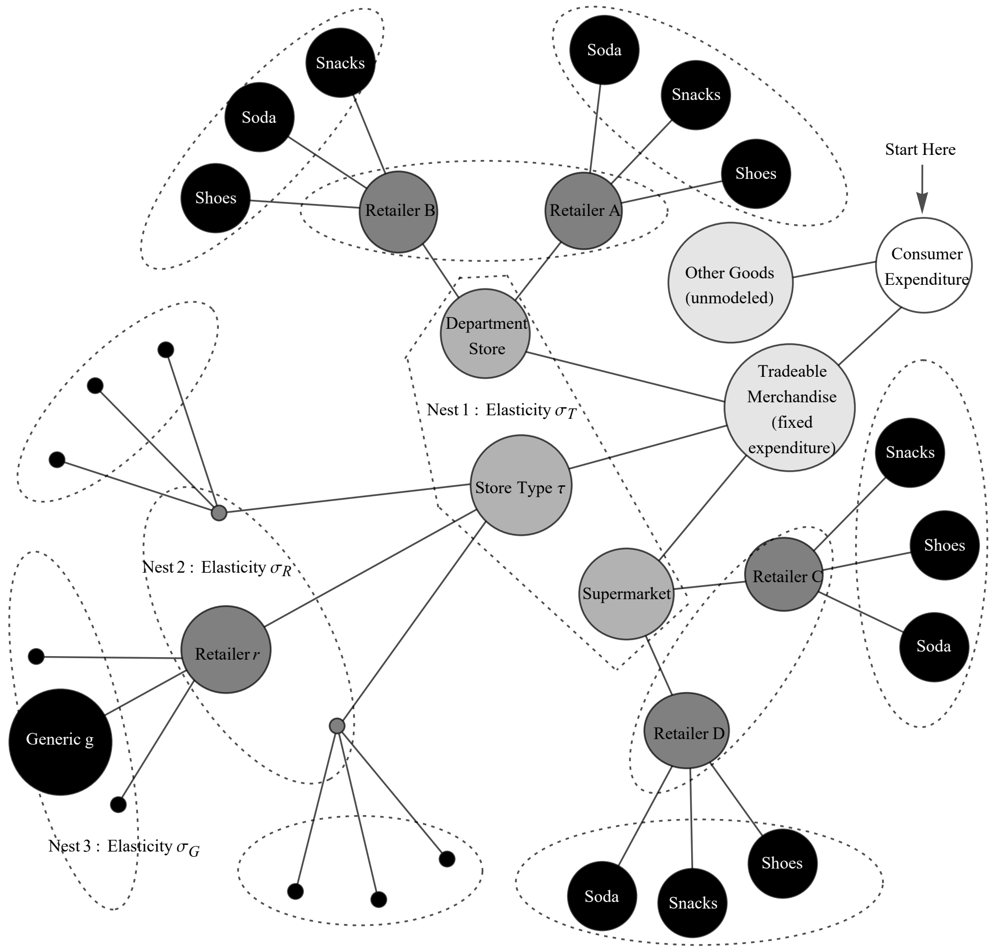
Several papers that work with flexible markups have discussed that nested CES preferences need that the outermost nest is Cobb-Douglas such that the expenditure is constant and producers do not use their market power to affect aggregate spending.[14] The model in this paper can be thought of as one of those, with a 4th nest that is Cobb-Douglas and has an exogenous constant fraction of the total expenditure spent in the tradeable merchandise goods consumption bundle that will be modeled, and the other fraction of total expenditure unmodeled (see figure 2 for a visualization of the preference structure).

3.1 Consumers

Each period, consumers in location ℓ can purchase their goods in any of the T types of store (indexed with τ). Within each type of store (in the data, one type of store is convenience store), consumers choose the retailer (indexed with $r \in R_{\tau\ell}$) where they will buy their goods. Once the retailer of each type of store is chosen, the consumers choose the generic product (indexed with $g \in G_{r\tau\ell}$) they want to purchase. The set of goods available in each retailer are not necessarily neither disjoint or the same.

As it is standard with nested CES preferences, consumers solve a three-stage problem. In the first stage, given a fixed amount of composite goods to be purchased on retailer r of type τ in location ℓ, consumers choose how much of each generic product to buy from each retailer. In the second stage, and given a fixed amount of composite goods to be purchased from each type of retailer, they choose how to allocate expenditure on each retailer of a certain type. In the final stage, for any level of expenditure, consumers choose how much to allocate to every type of store. Expenditure is fixed no matter what prices are faced by the consumers.

[14] See Hottman et al. (2016) for an extensive analysis of this particular issue.



Note: Elaborated by the author given the model specification.

Figure 2: Nested CES preferences structure of the model. This diagram includes the possibility of an outermost Cobb-Douglas nest as discussed in Hottman et al. (2016) that is not modeled in this paper.

So, given a set of generic products $G_{r\tau\ell}$ in retailer r of retailer type τ in location ℓ,[15] the price $p_{gr\tau\ell}$ of generic products g, and given a fixed amount of composite purchases $q_{r\tau\ell}$ in the retailer, consumers choose how much to buy of generic g by CES aggregating their purchases:

$$q_{r\tau\ell} = \left(\sum_{g \in G_{r\tau\ell}} \left(\beta_{gr\tau\ell}\right)^{\frac{1}{\sigma_G}} \left(q_{gr\tau\ell}\right)^{\frac{\sigma_G - 1}{\sigma_G}} \right)^{\frac{\sigma_G}{\sigma_G - 1}} \tag{1}$$

[15]Henceforth, "retailer r of retailer type τ in location ℓ" will just be "retailer r" as it only belongs to one type of retailer in a location. Same goes for "retailer type τ in location ℓ " that will be henceforth called just "retailer type τ"

where $\beta_{gr\tau\ell}$ is the preference parameter for generic good g when it is specifically found in retailer r and σ_G is the elasticity of substitution among generic products, with $\sigma_G > 1$. The demand for generic g in retailer r has the standard form

$$q_{gr\tau\ell} = \beta_{gr\tau\ell} \left(\frac{p_{gr\tau\ell}}{p_{r\tau\ell}} \right)^{-\sigma_G} q_{r\tau\ell} \tag{2}$$

where $p_{r\tau\ell} = \left(\sum_{g \in G_{r\tau\ell}} \beta_{gr\tau\ell} \left(p_{gr\tau\ell} \right)^{1-\sigma_G} \right)^{\frac{1}{1-\sigma_G}}$ is the ideal price index for the consumer when shopping in retailer r. In the second stage, consumers take the price index of each retailer and decide how much to buy from each retailer of each type. From the perspective of the consumer, the retailers are imperfect substitutes, either because they carry different generic products or because of amenity considerations.[16] Once the first stage is solved, consumers buy (a composite of) products from all the retailers of the same type and combine them into a composite good of retailer type, $q_{\tau\ell}$. The aggregation is

$$q_{\tau\ell} = \left(\sum_{r \in R_{\tau\ell}} \left(\beta_{r\tau\ell} \right)^{\frac{1}{\sigma_R}} \left(q_{r\tau\ell} \right)^{\frac{\sigma_R - 1}{\sigma_R}} \right)^{\frac{\sigma_R}{\sigma_R - 1}} \tag{3}$$

where $q_{r\tau\ell}$ measures the consumption of goods purchased in retailer r. The elasticity of substitution between retailers is σ_R with $1 < \sigma_R < \sigma_G$ and the retailer amenity parameter is $\beta_{r\tau\ell}$. The demand products of retailer r has the standard form

$$q_{r\tau\ell} = \beta_{r\tau\ell} \left(\frac{p_{r\tau\ell}}{p_{\tau\ell}} \right)^{-\sigma_R} q_{\tau\ell} \tag{4}$$

where $p_{\tau\ell} = \left(\sum_{r \in R_{\tau\ell}} \beta_{r\tau\ell} \left(p_{r\tau\ell} \right)^{1-\sigma_R} \right)^{\frac{1}{1-\sigma_R}}$ is the ideal price index for the consumer when shopping at retailer type τ. In the final stage, consumers combine all the bundles and derive

[16] Amenity considerations are also not modeled in this paper, but include such things as the proximity/access to the store and idiosyncratic preferences over types of stores (such as shopping in supermarkets vs. convenience stores).

utility from consuming bundles from all the store types. The utility function is

$$U_\ell = q_\ell = \left(\sum_{\tau=1}^{T} (\beta_{\tau\ell})^{\frac{1}{\sigma_T}} (q_{\tau\ell})^{\frac{\sigma_T - 1}{\sigma_T}} \right)^{\frac{\sigma_T}{\sigma_T - 1}} \tag{5}$$

where $q_{\tau\ell}$ measures the consumption of goods purchased in store type τ. The elasticity of substitution between store types is σ_T with $1 < \sigma_T < \sigma_G$ and the store type amenity parameter is $\beta_{\tau\ell}$. With retailer price index $p_{\tau\ell}$ (in the next subsection it will be possible to see how $q_{\tau\ell}$ is itself a composite of generic goods, and $p_{r\ell}$ is the ideal price index of that composite good), the budget constraint is simply

$$\sum_{\tau=1}^{T} p_{\tau\ell} q_{\tau\ell} \leq E_\ell \tag{6}$$

where E_ℓ is the total expenditure in location ℓ. Solving the consumer problem, I get the standard result that the demand for products from store type τ is linear in (nominal) expenditure.

$$q_{\tau\ell} = \beta_{\tau\ell} \left(\frac{p_{\tau\ell}}{p_\ell} \right)^{-\sigma_T} \frac{E_\ell}{p_\ell} \tag{7}$$

where $p_\ell = \left(\sum_{\tau=1}^{T} \beta_{\tau\ell} (p_{\tau\ell})^{1-\sigma_T} \right)^{\frac{1}{1-\sigma_T}}$ is the ideal price index. This three-stage problem implies that the demand for any generic g in terms of generic prices (which are retail specific meaning that a beer is an imperfect substitute of the same exact beer if that same beer is sold in another retailer), retail price indices, retailer type price indices and location level price indices is

$$q_{gr\tau\ell} = \beta_{gr\tau\ell} \beta_{r\tau\ell} \beta_{\tau\ell} \left(p_{gr\tau\ell} \right)^{-\sigma_G} (p_{r\tau\ell})^{\sigma_G - \sigma_R} (p_{\tau\ell})^{\sigma_R - \sigma_T} (p_\ell)^{\sigma_T - 1} E_\ell \tag{8}$$

This last equation is the base of everything that follows, and the derivatives of all the objects in the right hand side is what determines the result that the markup is flexible. Notice that nothing has been stated about the sign of $\sigma_R - \sigma_T$. This is not crucial to show that ERPT is estimated with bias because markups are flexible independent of the sign. I now briefly discuss the implications of different signs. Assume $p_{gr\tau\ell}$ to be fixed. If $\sigma_R > \sigma_T$ then an increase in the price index of supermarkets makes it more attractive to buy the generic product in a certain supermarket because the relative price decreased. But if $\sigma_R < \sigma_T$, then an increase in the price index of supermarkets reduces the demand for the generic product because of the crowding out effect that a reduction in the sales of supermarkets dominates the reduction of the relative price.

The generic own price elasticity within retailer is

$$\frac{d\log q_{gr\tau\ell}}{d\log p_{gr\tau\ell}} = -\sigma_G + (\sigma_G - \sigma_R + (\sigma_R - \sigma_T + (\sigma_T - 1)\, s_{\tau\ell})\, s_{r\tau\ell})\, s_{gr\tau\ell} \tag{9}$$

while the cross-price elasticity within store is

$$\frac{d\log q_{g'r\tau\ell}}{d\log p_{gr\tau\ell}} = (\sigma_G - \sigma_R + (\sigma_R - \sigma_T + (\sigma_T - 1)\, s_{\tau\ell})\, s_{r\tau\ell})\, s_{g'r\tau\ell} \tag{10}$$

where $s_{gr\tau\ell}$ is the expenditure share in generic g conditional on buying in retailer r, $s_{r\tau\ell}$ is the share of expenditure in retailer r, and $s_{\tau\ell}$ is the expenditure share in store type τ. Here the assumption of having $\sigma_T < \sigma_G$ and $\sigma_R < \sigma_G$ becomes crucial. Since the products are substitutes, the cross-price elasticity is positive for any value of $s_{\tau\ell}$ and $s_{r\tau\ell}$ only if the following condition is satisfied:

$$s_{r\tau\ell}\,(s_{\tau\ell} + (1 - s_{\tau\ell})\,\sigma_T) + (1 - s_{r\tau\ell})\,\sigma_R < \sigma_G \tag{11}$$

which requires $\sigma_T < \sigma_G$ and $\sigma_R < \sigma_G$. The own-price elasticity for any value of $s_{\tau\ell}, s_{r\tau\ell}, s_{gr\tau\ell}$ is negative only if the following condition is satisfied:

$$s_{r\tau\ell}\,(s_{\tau\ell} + (1 - s_{\tau\ell})\,\sigma_T) + (1 - s_{r\tau\ell})\,\sigma_R > 0 \tag{12}$$

which is trivially true if $\sigma_T, \sigma_R > 0$ (and even more so for $\sigma_T, \sigma_R > 1$).

3.2 Retailers

Each period, the retailers of each type τ have a fixed menu $G_{r\tau\ell}$ of final goods to sell. Then, they solve a two-stage problem. First, the retailers of type τ buy all their generic goods $q_{ogr\tau\ell}$ from the producers (for example, a bottle of beer). For notation purposes, the index o is added to separate it from when the generic product is bought by consumers. Then the retailers add value using a series of inputs $q_{gr\tau\ell i}$ (indexed by i), so it becomes a final good $Q_{gr\tau\ell}$ (a bottle of cold beer in a convenience store). The value they add to the generic good generates costs, and the technology to add value to the generic in order to sell it as a final good is

$$Q_{gr\tau\ell} = \left(\sum_{i \in I_{gr\tau\ell}} \left(\nu_{gr\tau\ell i}\right)^{\frac{1}{\eta}} \left(q_{gr\tau\ell i}\right)^{\frac{\eta-1}{\eta}} + \left(\nu_{ogr\ell}\right)^{\frac{1}{\eta}} \left(q_{gr\tau\ell o}\right)^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}} \tag{13}$$

where $q_{igr\ell}$ is the demand of input i (electricity, labor, etc.) and $q_{ogr\ell}$ is the demand of the generic $g \in G_{r\tau\ell}$ itself. The elasticity of substitution is $\eta < 1$, which means that the inputs are imperfect complements, and $\nu_{igr\ell}$ is the intensity parameter in the technology to add value to the generic. Assuming imperfect complements implies that both a higher intensity or a higher input price raise the share of the retailer cost on that input. The minimum cost to be able to transform the generic into a final good gives the retailer cost, $c_{gr\tau\ell}$, which solves

$$c_{gr\tau\ell} = \left(\sum_{i \in I_{gr\tau\ell}} \nu_{gr\tau\ell i} \left(p_{gr\tau\ell i}\right)^{1-\eta} + \nu_{gr\tau\ell o} \left(p_{gr\tau\ell o}\right)^{1-\eta} \right)^{\frac{1}{1-\eta}} \tag{14}$$

During the second step, since the retailer cannot instantaneously change the set of generic products to sell, the retailer competes with the rest of the retailers, taking both their own set of generics as fixed as well as the set of generics of the other retailers (summarized by their price indices). The retailer chooses prices in order to maximize profits, taking c_{grc} as given from the first stage:

$$\max_{p_{gr\tau\ell}} \sum_{g \in G_{r\tau\ell}} \left(p_{gr\tau\ell} - c_{gr\tau\ell}\right) q_{gr\tau\ell} \tag{15}$$

And the first order condition for the optimal price $p_{gr\tau\ell}$ for each g implies

$$q_{gr\tau\ell} + \sum_{g' \in G_{r\tau\ell}} \left(p_{g'r\tau\ell} - c_{g'r\tau\ell}\right) \frac{\partial q_{g'r\tau\ell}}{\partial p_{gr\tau\ell}} = 0 \tag{16}$$

which can be rearranged to:

$$1 + \sum_{g' \in G_{r\tau\ell}} \left(\frac{p_{g'r\tau\ell} - c_{g'r\tau\ell}}{p_{g'r\tau\ell}}\right) \left(\frac{\partial q_{g'r\tau\ell}}{\partial p_{gr\tau\ell}} \frac{p_{gr\tau\ell}}{q_{g'r\tau\ell}}\right) \left(\frac{p_{g'r\tau\ell} q_{g'r\tau\ell}}{p_{gr\tau\ell} q_{gr\tau\ell}}\right) = 0 \tag{17}$$

Noticing that $\frac{p_{g'r\tau\ell} q_{g'r\tau\ell}}{p_{gr\tau\ell} q_{gr\tau\ell}} = \frac{s_{g'r\tau\ell}}{s_{gr\tau\ell}}$, define the Lerner Index as $m_{gr\tau\ell} = \frac{p_{gr\tau\ell} - c_{gr\tau\ell}}{p_{gr\tau\ell}}$ and, without loss of generality, assume that the cardinality of the set $G_{r\tau\ell}$ equals G. Substituting with equation 9 and equation 10 this implies, in matrix form

$$\begin{pmatrix} -\sigma_G + \gamma s_{1r\tau\ell} & \gamma s_{2r\tau\ell} & \cdots & \gamma s_{Gr\tau\ell} \\ \gamma s_{1r\tau\ell} & -\sigma_G + \gamma s_{2r\tau\ell} & \cdots & \gamma s_{Gr\tau\ell} \\ \vdots & \vdots & \ddots & \vdots \\ \gamma s_{1r\tau\ell} & \gamma s_{2r\tau\ell} & \cdots & -\sigma_G + \gamma s_{Gr\tau\ell} \end{pmatrix} \begin{pmatrix} m_{1r\tau\ell} \\ m_{2r\tau\ell} \\ \vdots \\ m_{Gr\tau\ell} \end{pmatrix} = \begin{pmatrix} -1 \\ -1 \\ \vdots \\ -1 \end{pmatrix} \tag{18}$$

where $\gamma = \sigma_G - s_{r\tau\ell}\left(s_{\tau\ell} + (1 - s_{\tau\ell})\,\sigma_T\right) - (1 - s_{r\tau\ell})\,\sigma_R$. This leads to

Proposition 1

The optimal markup for the retailer selling generic good g in retailer r of retailer type τ in location ℓ is independent of the generic good, is larger than 1 and equals to $\frac{\varepsilon_{r\tau\ell}}{\varepsilon_{r\tau\ell} - 1}$ where $\varepsilon_{r\tau\ell} = s_{r\tau\ell}\left(s_{\tau\ell} + (1 - s_{\tau\ell})\,\sigma_T\right) + (1 - s_{r\tau\ell})\,\sigma_R$.

Proof:

Let $A = \begin{pmatrix} -\sigma_G + \gamma s_{1r\tau\ell} & \cdots & \gamma s_{Gr\tau\ell} \\ \vdots & \ddots & \vdots \\ \gamma s_{1r\tau\ell} & \cdots & -\sigma_G + \gamma s_{Gr\tau\ell} \end{pmatrix}$ be the GxG matrix of constants in the left-hand side of equation 18. It is trivial to show that $A\,(1, 1, ..., 1)^T = (\gamma - \sigma_G, \gamma - \sigma_G, ..., \gamma - \sigma_G)^T$. This means that $\gamma - \sigma_G$ is an eigenvalue of the matrix A, and $(1, 1, ..., 1)^T$ is an eigenvector of the matrix A. Solving for $m_{gr\tau\ell}$ the system of equations in (18) implies finding a vector x that solves $Ax = (-1,-1,...,-1)^T$. Multiplying both sides by $\sigma_G - \gamma$ implies $A((\sigma_G - \gamma)x) = (\gamma - \sigma_G, \gamma - \sigma_G, ..., \gamma - \sigma_G)^T$ which means that $x = \frac{(1,1,...,1)^T}{\sigma_G - \gamma}$. As all the rows of the matrix add up to the same constant $\gamma - \sigma_G$, this means that the only solution for this system of equations is $m_{gr\tau\ell} = m_{r\tau\ell} = \frac{1}{\varepsilon_{r\tau\ell}}$ where $\varepsilon_{r\tau\ell} = s_{r\tau\ell}(s_{\tau\ell} + (1 - s_{\tau\ell})\sigma_T) + (1 - s_{r\tau\ell})\sigma_R$.

This ends the proof.

This generalizes the standard result (see Atkeson and Burstein (2008)) that the within-retailer cannibalization effect is exactly offset by the between-retailer substitution, which means a constant markup for every generic product within a retailer, and this markup depends on the elasticity of substitution between retailers and does not depend on the elasticity of substitution between generic products.[17]

$$M_{gr\tau\ell} = \frac{p_{gr\tau\ell}}{c_{gr\tau\ell}} = M_{r\tau\ell} = \frac{\varepsilon_{r\tau\ell}}{\varepsilon_{r\tau\ell} - 1} \tag{19}$$

Notice that $\varepsilon_{r\tau\ell} > 1$ for any $s_{r\tau\ell}, s_{\tau\ell}$ the model requires $\sigma_T, \sigma_R > 1$. In international trade literature, the term $\varepsilon_{r\tau\ell}$ is usually called perceived elasticity, and producers exploit the fact that they operate in a market where their product has a lower perceived elasticity to charge higher markups. In this setting, being a retailer from a store type with a large market share implies lower perceived elasticity for any values of σ_T and σ_R, but being a large retailer or small retailer within your store type does not give any ex-ante predictions about the perceived elasticity without knowing the values of σ_T and σ_R.

3.3 Producers

For simplicity, I will assume that at each location, retailers purchase the generic goods from a continuum of producers at a price that does not depend on the location nor the store type nor the retailer identity, $p_{gr\tau\ell o} = p_{go}$. There is no strategic interaction between producers and retailers. From the point of view of the retailers, input prices are completely exogenous.

[17]The mechanical process by which if a store reduces the price of one product then it reduces the demand for the rest of its own products is called "cannibalization effect".

For estimation purposes, I will assume that all input prices can be expressed as price indices of known prices for the econometrician, multiplied by some non-/parameterized constant. This means that all the retailer log-cost changes can be expressed as a weighted sum of all the value added log-price index changes (exchange rate, foreign and local wages, transport costs, foreign and local electricity tariffs, foreign and local land rent, tariffs, etc):

$$
\begin{aligned}
d\log c_{gr\tau\ell} &= s_{gr\tau\ell o} d\log p_{go} + \sum_{i\in I_{gr\tau\ell}} s_{gr\tau\ell i} d\log p_{gr\tau\ell i} \\
&= s_{gr\tau\ell o}\left(\sum_{j\in J_{gr\tau\ell o}} \omega_{jgr\tau\ell o} d\log p_{jgr\tau\ell}\right) + \sum_{i\in I_{gr\tau\ell}} s_{gr\tau\ell i}\left(\sum_{j\in J_{gr\tau\ell i}} \omega_{jgr\tau\ell i} d\log p_{jgr\tau\ell}\right) \\
&= \sum_{j\in J} \theta_{jgr\tau\ell} d\log p_{jgr\tau\ell} \qquad (20)
\end{aligned}
$$

where J is the set of inputs whose value added is imputed in the price, $p_{jr\tau\ell}$ is the price of value added inputs, and $\theta_{jgr\tau\ell}$ is the value added share.

3.4 Comparative statics and elasticity of markups

The model derives a set of predictions that can be tested in the data. In this paper I will assume that $\nu_{gr\tau\ell i}, \beta_{gr\tau\ell}, \beta_{r\tau\ell}, \beta_{\tau\ell}, \sigma_G, \sigma_R, \sigma_T, \eta$ are constant over time. This means that in equilibrium the only sources of variation of market shares, markups, etc. are the input prices in the retail production function of generic final goods, the number of products sold at each retailer, and the number of inputs in the value added by retailers. The elasticity of the markup with respect to the generic input price is positive and equal to the share of the generic as an input in the total cost of the retailer to produce one unit of generic as final good

$$
\frac{\partial \log M_{r\tau\ell}}{\partial \log p_{go}} = \nu_{gr\tau\ell o}\left(\frac{p_{go}}{c_{gr\tau\ell}}\right)^{1-\eta} = s_{gr\tau\ell o} \qquad (21)
$$

This share is independent of both the market share of the retailer in its store type, as well as the market share of the store type in the economy. It also does not depend on any elasticity of substitution. Notice that $\frac{M_{r\tau\ell}}{p_{go}}$ also measures the value added by the retailer, because it is exactly the ratio between the price at which consumers will buy the generic and the price at which retailers bought the generic. For the same reason, the elasticity of the markup with respect to any input in the production of a final generic has the same form too

$$\frac{\partial \log M_{r\tau\ell}}{\partial \log p_{gr\tau\ell i}} = \nu_{gr\tau\ell i} \left(\frac{p_{gr\tau\ell i}}{c_{gr\tau\ell}} \right)^{1-\eta} = s_{gr\tau\ell i} \tag{22}$$

Substituting input prices with value added price indices the analogous expression holds:

$$\frac{\partial \log M_{r\tau\ell}}{\partial \log p_{jgr\tau\ell}} \quad = \quad \theta_{jgr\tau\ell} \tag{23}$$

This identifies the elasticities of the input cost on prices, one of those inputs being usually the exchange rate, and the corresponding elasticity being the ERPT. In fact, equation 23 is the baseline identification for ERPT in almost every paper ever written that uses micro data. The model also predicts that the elasticity of the markup with respect to the store-type relative price with respect to other types of stores $\frac{p_{\tau\ell}}{p_{\ell}}$ is negative

$$\frac{\partial \log M_{r\tau\ell}}{\partial \log \left(\frac{p_{\tau\ell}}{p_{\ell}} \right)} = -\frac{(\sigma_T - 1)^2 s_{r\tau\ell} s_{\tau\ell}}{(\varepsilon_{r\tau\ell} - 1)\, \varepsilon_{r\tau\ell}} \tag{24}$$

Notice that the markup would be inflexible to the retailer type relative price index if preferences were Cobb-Douglas for retail types, that is, if σ_T equals 1. This becomes important when, for example, one of the sources of variation of the relative price $\frac{p_{\tau\ell}}{p_{\ell}}$ is that store type τ increased the number of products they sell. This can immediately change price indices even without having any input price changes.

The elasticity of the markup with respect to their own price index relative to the same store type price index $\frac{p_{r\tau\ell}}{p_{\tau\ell}}$ is negative if retailers are better substitutes within store types than store types between themselves or positive if store types are better substitutes than retailers but the store type has a small share of the market, as it can be seen in the following expression

$$\frac{\partial \log M_{r\tau\ell}}{\partial \log\left(\frac{p_{r\tau\ell}}{p_{\tau\ell}}\right)} = -\frac{(\sigma_R - 1)\, s_{r\tau\ell}}{(\varepsilon_{r\tau\ell} - 1)\,\varepsilon_{r\tau\ell}} \left(\sigma_R - \left(s_{\tau\ell} + (1 - s_{\tau\ell})\,\sigma_T\right)\right) \tag{25}$$

Also notice that this markup would be inflexible if preferences over retailers within store types were Cobb-Douglas ($\sigma_R = 1$). If the retailer is infinitesimal within store types, $s_{r\tau\ell} = 0$, and preferences are not Cobb-Douglas, then the markup is inelastic (the markup equals $\frac{\sigma_R}{\sigma_R - 1}$), and if the store type is infinitesimal with respect to the rest of the stores, $s_{\tau\ell} = 0$, then the markup equals $\frac{s_{r\tau\ell}\sigma_T + (1-s_{r\tau\ell})\sigma_R}{s_{r\tau\ell}(\sigma_T - 1) + (1-s_{r\tau\ell})(\sigma_R - 1)}$ and is inelastic to the store type price index (relative to the overall price index), but elastic to the store price index relative to the store type price index. The markup and the elasticity of the markup does not depend on the generic product and does not depend on the elasticity between generic products.

3.5 Calculating the exchange rate pass-through

The previous subsection of this document highlights an important issue that must be considered to estimate the elasticities of markups with respect to input prices: a larger share of the store type and share of the retailer within the store type increases the markup but increases its flexibility. Taking this model as the true data generating process, and holding all preference parameters constant, this markup flexibility implies that the time series variations of the retailer prices can be expressed as the sum of three components: the usual cost-push component which is completely inflexible from the point of the retailer, then a first flexible component whose magnitude depends on the store-type importance in the location, and a second flexible component whose magnitude depends on the retailer importance in the store-type:

$$\begin{aligned} d\log p_{gr\tau\ell} &= \underbrace{d\log c_{gr\tau\ell}}_{\text{cost-push}} \\ &\quad \underbrace{-\frac{(\sigma_T-1)^2 s_{r\tau\ell}s_{\tau\ell}}{(\varepsilon_{r\tau\ell}-1)\,\varepsilon_{r\tau\ell}} d\log\left(\frac{p_{\tau\ell}}{p_\ell}\right)}_{\text{store-type importance in the location}} \\ &\quad \underbrace{-\frac{(\sigma_R-1)\,s_{r\tau\ell}}{(\varepsilon_{r\tau\ell}-1)\,\varepsilon_{r\tau\ell}}\left(\sigma_R-(s_{\tau\ell}+(1-s_{\tau\ell})\,\sigma_T)\right) d\log\left(\frac{p_{r\tau\ell}}{p_{\tau\ell}}\right)}_{\text{retailer importance in the store-type}} \end{aligned} \tag{26}$$

So, using the price data to estimate the cost functions of the retailers without correcting for the store type relative price (or controlling for store type) will bias the results, since the true prices are flexible to the store type shares but have mean zero. The change in price as a proxy for change in costs (see equation 23), however, perfectly estimate the ERPT (or any other elasticity with respect to input prices) in two special cases: when the retailer market share is zero and/or when preferences over store types and retailers are Cobb-Douglas. When this happens then the markup is inflexible, meaning $d\log M_{r\tau\ell}=0$ but most importantly all price changes can be mapped to marginal cost changes

$$d\log p_{gr\tau\ell} = d\log c_{gr\tau\ell} \tag{27}$$

Notice that equation 27 is the baseline expression for most of the ERPT estimation equations in recent literature (see Gopinath and Itskhoki (2010), Kochen and Sámano (2016), Baley et al. (2016), and Baharumshah et al. (2017)). Suppose that $s_{r\tau\ell}=0$ for every retailer and that you want to estimate the input price elasticities:

$$\begin{aligned} d\log p_{gr\tau\ell} &= d\log c_{gr\tau\ell} \\ &= s_{gr\tau\ell o} d\log p_{gr\tau\ell o} + s_{gr\tau\ell i}\cdot d\log p_{gr\tau\ell i} + \varepsilon_{gr\tau\ell} \\ &= \theta_{jgr\tau\ell}\cdot d\log p_{jr\tau\ell} + \varepsilon_{gr\tau\ell} \end{aligned} \tag{28}$$

Using all the data on prices from the CPI and on value added input prices (such as the exchange rate, international commodity prices, etc.), a simple linear regression gives the best estimate of $\theta_{jgr\tau\ell}$, assuming $\varepsilon_{gr\tau\ell}$ has mean zero and is uncorrelated with $d\log p_{jr\tau\ell}$. Relaxing that $s_{r\tau\ell}=0$, from equation 26 I get

$$\begin{aligned} d\log p_{gr\tau\ell} \quad &= \quad \underbrace{-\frac{(\sigma_R-1)\,s_{r\tau\ell}}{(\varepsilon_{r\tau\ell}-1)\,\varepsilon_{r\tau\ell}}\left(\sigma_R-(s_{\tau\ell}+(1-s_{\tau\ell})\,\sigma_T)\right)}_{\text{retailer importance}}\underbrace{d\log\left(\frac{p_{r\tau\ell}}{p_{\tau\ell}}\right)}_{\text{mean zero}} \\ &+\underbrace{\theta_{jgr\tau\ell}\cdot d\log p_{jr\tau\ell}}_{\text{cost-push}}-\underbrace{\frac{(\sigma_T-1)^2\,s_{r\tau\ell}s_{\tau\ell}}{(\varepsilon_{r\tau\ell}-1)\,\varepsilon_{r\tau\ell}}}_{\text{store-type importance}}\underbrace{d\log\left(\frac{p_{\tau\ell}}{p_\ell}\right)}_{\text{mean zero}}+\varepsilon_{gr\tau\ell} \qquad (29)\end{aligned}$$

and if $\varepsilon_{gr\tau\ell}$ is assumed to be mean zero and uncorrelated with $d\log p_{jr\tau\ell}, d\log\left(\frac{p_{\tau\ell}}{p_\ell}\right), d\log\left(\frac{p_{r\tau\ell}}{p_{\tau\ell}}\right)$ then it is possible to obtain consistent estimators of $\theta_{jgr\tau\ell}$. Notice that the population mean of $d\log\left(\frac{p_{\tau\ell}}{p_\ell}\right)$ and $d\log\left(\frac{p_{r\tau\ell}}{p_{\tau\ell}}\right)$ are both zero. This means that in theory, equation 28 does not satisfy the Gauss-Markov conditions, because $\varepsilon_{gr\tau\ell}$ is correlated with $d\log p_{jr\tau\ell}$ before observing $d\log\left(\frac{p_{r\tau\ell}}{p_{\tau\ell}}\right)$ and $d\log\left(\frac{p_{\tau\ell}}{p_\ell}\right)$. This is a classic omitted variable bias which implies that all the estimates of $\theta_{jgr\tau\ell}$ will be inconsistent and as the sample grows, converge to biased values. This is the main point of the paper: equation 28 does not work if the data are collected in retailers with some market power. The correction is using equation 29. The rest of this paper will stop being a discussion on flexible markups and only discuss the bias.

4 Data

In order to test this model I need to construct the time series of the prices charged by the retailers $p_{gr\tau\ell}$ as well as the retailer identity. I also need time series of the input prices $p_{jr\tau\ell}$. To estimate costs, I will use the exchange rate and the usual macroeconomic data for statistical *cost-push* analysis, which were obtained from Banco de México.[18] The main sources of data are the CPI data from June 2009 to June 2018. I briefly describe the CPI data next.

[18]The usual macroeconomic data for cost-push analysis include the electricity price index, IMF commodities price index, formal wages, and Mexican treasury bonds (CETES).

I have access to very detailed confidential INEGI micro-data from the CPI from June 2009 to June 2018. The entire data set has 23 million price observations. Each price observation has (coded) information on the store, the product description, the generic, the date, if it was on sale, and so on. Following Kochen and Sámano (2016), and in order to have contemporaneous macroeconomic variables for the econometric *cost-push* analysis, I restrict the complete sample to the last observation of the month, which typically occurred the last week of the month. This leaves 10.88 million observations for the analysis.[19] The Census of Population of 2010 indicates that the population of the 476 municipalities that constitute the 46 "cities" where the CPI data are collected add up to 85.4 million people, which was 75.67 percent of the population and 88.06 percent of the total urban population of 2010. The same municipalities, using CONEVAL[20] data for 2010, accounted 87.64 percent of the household income in Mexico.

Then, following Kochen and Sámano (2016), I restrict the monthly sample to the tradeable merchandise goods of the CPI, which, among other things, is less sensitive to taste shocks. The tradeable merchandise goods monthly subset has a total of 7.92 million price observations, and the variety of products amounts to 56.8 percent of the weight of the CPI. I take note of the product, the date (month) that the price was collected, the city, and the type and name of the store where the product is sold.[21] I then match every price of each product in every store with the price of the same good in the same store in the past, and get the accumulated change in the price, but also the change in the pesos/dollar exchange rate, average wages, electricity tariffs, etc. In the estimation, I use various lengths of time intervals to test whether the data start showing if fixing taste parameters over time is relevant, but I always

[19]The entire data set has bi-weekly (or weekly, for agricultural products) prices, so mechanically more than half of the sample is dropped.

[20]CONEVAL is the acronym of Consejo Nacional de Evaluación de la Política de Desarrollo Social, the public institution in charge of generating information on social policies and poverty measurements in Mexico. One of their tasks is calculating statistically significant municipal household income data every 5 years.

[21]There are 8 types of stores in the CPI data set: supermarket, public market, specialized store, tianguis, convenience store, department store, price club and subsystem (an internal INEGI type of store used mostly for real estate and government controlled tariffs). There are no subsystem stores in the tradeable merchandise subset of prices. Tianguis was removed from the data set because very few products had reasonably long time series of prices. Price clubs were used in the estimation but the results are not reported due to confidentiality of the data.

remove all the observations that had product price change equal to zero because otherwise the error term is correlated with the regressors (they cancel each other out perfectly using a linear combination). They are all reported.

From the data, only a very small set of price changes are dropped, because as part of their constitutional task of measuring inflation in Mexico, INEGI's methodology to collect prices involves observing comparable products over time. This leads very frequently to cases where the price of the same product is collected in the same store for a long period of time. The Consumer Price Index (CPI) data from INEGI show that between June of 2009 and June of 2018 the median product-store combination of consecutive price observations was 13.5 months, and the average was 36 months. Table 1 contains summary statistics of the data that was used in this document, and compares it with the entire data set which includes non tradeable goods and utility costs indices (the latter ones have governmental price controls).

Data set statistic	All CPI products, monthly	Tradeable Merchandise, monthly
Observations that are price change	20.08 percent	21.13 percent
Median product-store combinations length	14 months	14 months
Average product-store combinations length	35 months	38 months
Number of observations	10,883,342	7,923,526
Weight in CPI	100 percent	56.8 percent

Note: Statistics elaborated by the author with data from INEGI.

Table 1: The entire monthly CPI data set compared with the one that is used in this document

The CPI has $T = 6$ store types in the data set: specialized store, convenience store, department store, public market, price club, and supermarket. The data set that I had access to does not specify the address of the store, so if two products were price-quoted in the same city, in the same store type and store name, I will consider it to be in the same store (or in terms of the parameters of this model, a *larger* store). The data shows there are 246 generic product categories (from a total of more than 291,000 different products). From a probabilistic point of view, since INEGI's sample was designed to match the expenditure shares from the ENIGH survey, more products in the same store imply that the store has a larger share within product categories.[22] Table 2 shows a summarized table of the data categories.

5 Estimation and Results

In this section I briefly describe the estimating equations to get the input price elasticities, including the ERPT. First, I start with some methodological considerations, in order to pin down the estimation procedure, as well as what types of results should be expected. In the model, I assume that prices are flexible and that every retailer is a multi-final goods producer of generic goods (for example, bottles of cold beer and dishwater soap in a convenience store) facing exogenous[23] prices from the producers of every generic product (for example, bottles of beer and dishwater soap) as well as exogenous input prices (wages, electricity, etc.). With nested CES preferences, I find that for every retailer, the optimal price for each of the products they sell involves setting a constant markup in every good in the store that depends on the market share of the retailer in its own store type and of the store type in the whole economy. The markup is constant because the within-retailer cannibalization effect is exactly offset by the between-retailer substitution; and this markup does not depend on the elasticity of substitution between the goods sold in the store (which is a standard result in Atkeson and Burstein (2008) and Hottman et al. (2016) from the producer point of view, and more recently studied by Eaton et al. (2016) and Atkin et al. (2018) from the retailer point of view). My framework only uses CPI data and hence is widely applicable because the CPI price observations allow to do this by store type, but other data sets that contain more specific information such as the neighborhood can also be used in other contexts. Also, most data sets with quantities and prices at the household level (where the shares can be observed over time) hardly capture more than 30 percent of the CPI goods so the data set used in this paper is somewhat restricted in identifying a rich set of store characteristics, but has a wide set of consistent goods, and long time series for the same stores.

[22]ENIGH is the acronym of Encuesta Nacional de Ingreso y Gasto de los Hogares, a household level survey published by INEGI with very detailed information on income and expenditure.

[23]This can be thought of as the producer not being able to discriminate using pricing-to-market.

			Generic Categories	Weight	Quoting Frequency	Product Varieties	Observations
Core			206	50.2	Weekly and Bi-weekly	263,517	6,424,507
	Merchandise		176	33.9	Weekly and Bi-weekly	245,782	5,599,392
		Food commodities	67	14.7	Weekly	45,227	1,701,029
		Non-food commodities	109	19.2	Weekly and Bi-weekly	200,555	3,898,363
	Services		30	16.4	Weekly and Bi-weekly	17,735	825,115
		Housing	2	2	Weekly and Bi-weekly	1,867	76,572
		Other Services	28	14.4	Weekly and Bi-weekly	15,868	748,543
Non-Core			40	8.43	Weekly and Bi-weekly	27,778	1,724,743
	Agriculture		40	8.43	Weekly	27,778	1,724,743
		Fruits and vegetables	32	3.6	Weekly	18,709	1,233,203
		Meats, poultry, fish, and eggs	8	4.9	Weekly	9,069	491,540

Note: Statistics elaborated by the author with data from INEGI.

Table 2: Descriptive statistics of the components of the CPI

I use a series of reduced form expressions where the store information is explicitly accounted for and initially compare the results with what can be called the "baseline case", which is without the store information. The estimation for the elasticity of the value added inputs in equation 29 is

$$d\log p_{gr\tau\ell_t} = \theta_j \cdot d\log p_{j_t} + \alpha_t + \alpha_d + \alpha_g + \beta_{r\tau\ell} + \varepsilon_{gr\tau\ell_t} \tag{30}$$

where α_t is a date dummy (month-year), α_d indicate if the store offered the product for a discount, α_g indicates generic product fixed effects, $d\log p_{j_t}$ is the log-change in the cost-push component of the regression, one such j being the exchange rate.[24] The dummies are meant to control for possible variations in the taste parameters over time. The coefficients $\beta_{r\tau\ell}$ identify the retailer (within its store type) at the city level. The model predicts that $\beta_{r\tau\ell}$ are non-zero (and the sign depends on whether the sector is more or less concentrated), but more importantly, that the estimates for θ_j are smaller if there are no dummies for the store type or retailers. The results are in table 3. I use 6 months as a baseline time interval, and removed all the observations that had $d\log p_{gr\tau\ell_t} = 0$. The estimators obtained after removing the observations with zero price change are known as conditional pass-through estimators. Retailers that do not belong to a chain are classified as such because the name of the store only appears once per month in each city-store type pair. Also, the uniform markups are set by city because there are variations in the market share of the stores in the cities, even if the costs are identical for all cities.

I now guide the reader towards the important results of table 3. First, comparing the exchange rate coefficient (the measured ERPT) between columns (1) and (2). The latter is 340 basis points larger than the former, and the only difference between the two regressions is that there are controls for the store types in the latter, which shows, first, that the store type dummies capture some of the variation in the ERPT, just as maybe any model that allows for store specific markups would predict. Second, it shows that in this case the total effect of not

[24]The cost-push components used in this paper are the same ones used in Kochen and Sámano (2016) and are the exchange rate, the electricity price index, IMF commodities price index, formal wages, and Mexican treasury bonds (CETES).

including the store types is negative, just as this model predicted. Then, columns (3) and (4) have the same exercise, now with generic product controls, which capture possible store-type differences so now the comparison is with exactly the same products. The difference is 320 basis points which again shows larger measured ERPT when the store characteristics are accounted for. The model explains around 10 percent of the price variation, which is standard in this literature. Also note that the coefficients on wages and electricity prices are all also positive and significant the interest rate (CETEs) coefficient is negative, and that these coefficients also grow when the regression controls for the store type.

	(1)	(2)	(3)	(4)
Exchange Rate	0.285***	0.319***	0.339***	0.371***
	(0.038)	(0.037)	(0.04)	(0.043)
Electricity Prices	0.572***	0.581***	0.582***	0.671***
	(0.067)	(0.066)	(0.066)	(0.079)
IMF Commodities Index	-1.783***	-1.811***	-1.818***	-1.861***
	(0.197)	(0.195)	(0.195)	(0.232)
Formal Wages	2.36***	2.37***	2.382***	2.446***
	(0.289)	(0.286)	(0.286)	(0.341)
CETEs	-0.136***	-0.139***	-0.139***	-0.134***
	(0.018)	(0.017)	(0.017)	(0.021)
Begin Sale	-0.171***	-0.167***	-0.167***	-0.172***
	(0.001)	(0.001)	(0.001)	(0.001)
During Sale	-0.036***	-0.031***	-0.03***	-0.042***
	(0.001)	(0.001)	(0.001)	(0.001)
End Sale	0.109***	0.112***	0.112***	0.11***
	(0.001)	(0.001)	(0.001)	(0.001)
Date	✓	✓	✓	✓
Generic Product			✓	✓
Chain Indicator x Store Type x City		✓		✓
Number of Observations	3,827,545	3,827,545	3,827,545	3,827,545
R^2	0.1122	0.1211	0.1208	0.1245

*** p<0.001, ** p<0.01, * p<0.05

Notes: The price change specification is given by $dlogp_{gr\tau\ell_t} = dp_{gr\tau\ell_t} - dp_{gr\tau\ell_{t-h}}$ where $h = 6$ months. The control variables (electricity prices, etc.) come from Kochen and Sámano (2016). The store types (convenience store, supermarket, public market, department store, price clubs and specialized store) are INEGI-generated. Price club data are used but not reported due to confidentiality. The cities are also INEGI-generated, and they are the 46 cities of the CPI data base. Price data from INEGI, cost-push data from Banco de México.

Table 3: ERPT with cost controls, product, city, and retailer type fixed effects.

5.1 Incorporating the model structure: infinitesimal stores

Next, I incorporate the model structure to test whether assuming that the taste parameters are constant can give insight to ERPT estimations. First, I calculate the ERPT for the stores that do not seem to be chains or franchises in the data.[25] The model predicts that if there are no controls for store type, the ERPT is different in those stores (because it is estimated without bias), and more importantly, that controlling for store type should not affect the estimations. So, for every retailer in the sample that does not belong to a chain or franchise, the estimation equation is identical to equation 30 and the results are in table 4. The model explains around 10 percent of the price variation.

The results suggest that the model explains the variations in the data in two dimensions. First, that controlling for store type does not affect the ERPT estimations, and second, that the ERPT is similar to the general ERPT (in the previous table) after controlling for store type.

For robustness of the results, next I substitute the store type fixed effects and add the changes in the relative price indices (store type relative to city, and retailer relative to store type). This helps to pin down if the assumption of fixing the preference parameters and only allowing input prices, number of inputs, and number of products to vary helps explain the variation in the data, and how much of the bias can be attributed to other factors, like the preference parameters. The price indices need to be interacted with city fixed effects, meaning that the heterogeneity in relative price index variations is explained by local fixed factors (in the scope of the model, by local preference parameters) and not by systematic improvements in store type productivity. The results are similar in qualitative terms so they are not shown in this version.

I can make use of the fact that I know the conglomerate that produces each product and also its nationality, in order to control for at least some proxies for the producer, using the fact that Hottman et al. (2016) have documented that there is quite significant variation in

[25] I am implicitly assuming that the retailers within a store type that do not belong to a chain have zero market share.

	(1)	(2)
Exchange Rate	0.375***	0.374***
	(0.042)	(0.043)
Electricity Prices	0.69***	0.681***
	(0.078)	(0.079)
IMF Commodities Index	-1.894***	-1.858***
	(0.228)	(0.232)
Formal Wages	2.446***	2.442***
	(0.336)	(0.341)
CETEs	-0.137***	-0.134***
	(0.021)	(0.021)
Begin Sale	-0.165***	-0.172***
	(0.001)	(0.001)
During Sale	-0.033***	-0.042***
	(0.001)	(0.001)
End Sale	0.107***	0.1***
	(0.001)	(0.001)
Date	✓	✓
Store Type		✓
Number of Observations	2,355,212	2,355,212
R^2	0.0992	0.1118

Errors clustered by store type - city

*** p<0.001, ** p<0.01, * p<0.05

Notes: The price change specification is given by $dlogp_{gr\tau\ell_t} = dp_{gr\tau\ell_t} - dp_{gr\tau\ell_{t-h}}$ where $h = 6$ months. The control variables (electricity prices, etc.) come from Kochen and Sámano (2016). The store types (convenience store, supermarket, public market, department store, price clubs and specialized store) are INEGI-generated. Price club data are used but not reported due to confidentiality. The cities are also INEGI-generated, and they are the 46 cities of the CPI data base. Price data from INEGI, cost-push data from Banco de México.

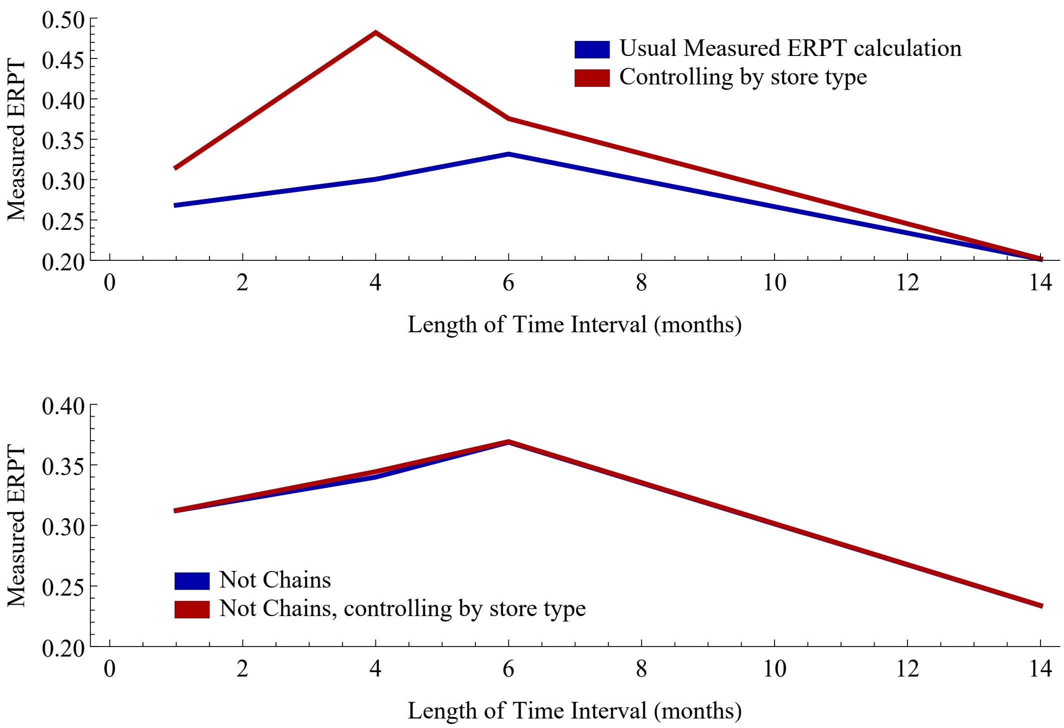
Table 4: ERPT with cost controls, product, city, and retailer type fixed effects. All stores that were found to be store chains were removed from the sample

the ERPT to the retailers depending on the producer share of the market. Some products have specifically no brand, agricultural products being the most common example. Those products were labeled as “generic conglomerate” and used as the base for the dummies of the conglomerate. Around 80 percent of the brands of the products in the tradeable merchandise CPI data set, including the generic conglomerate were found in IMPI’s data base, just above 8 million prices. The products whose brand was not located in the data set were dropped as it was not evident that grouping them as coming from a single unnamed producer or them being tens of thousands of individual producers would give any meaningful result. The results, controlling for generic are also almost identical quantitatively.

5.2 Different lengths of the time intervals

All the previous results are based on the fact that prices are observed every month but all price changes are observed after 6 months, and dropped if there are no changes. It is possible that all these results depend greatly on the length of the time frame chosen. In this subsection I relax the assumption that the time interval is 6 months and allow it to be any number of months between 1 and 14. As figure 3 shows, qualitatively the results are the same, although there are some differences. Note that in the long run (14 months) the ERPT seems to converge for every type of store, which means that eventually all the prices adjust and there is no bias when calculating the pass-through, but in the short run it is always the case that ERPT is lower when the estimation does not take into account the store type.[26] For the case of zero-measure stores, which for the data they are the ones that were not found to be a chain, the results are equivalent but at different levels: it makes no difference to control for store type. All the stores pass-through onto consumers the exchange rate variations irrespective of the store type at the exact same rate, it’s just that depending on the time frame, the rates vary over time.

[26]In Mexico wages are quite inflexible. When the regressions are performed over longer periods of time the coefficient for the wages goes up in detriment of the coefficient of the exchange rate. The usual way ERPT is calculated over h months is by having dummy variables of all the h months and adding them up. This representation is not useful to test this model since I want all variables to vary over the same period of time to be able to interpret the coefficients as elasticities.



Note: Price data from INEGI, cost-push data from Banco de México. The chain classification was done by the author.

Figure 3: Measured ERPT when changing the length of the time interval

6 Summary of the Results and Conclusion

The section above clearly suggests that the ERPT is estimated with bias when the store type is not included in the estimation. For the case of Mexico, this bias is downwards. Not even the generic product fixed effects of city can change this result. In fact, the average ERPT is almost unaffected when adding city and generic product controls. This implies that something at the retail level varies a lot by city and by generic product. This turns out to be the store types market share distribution, and in particular supermarkets and department stores seem to have a large enough concentration to dampen the measured ERPT by as much as 340 basis points over six months. This paper assumes that every retailer can buy from the producer at the same cost and analyzes the variation in the ERPT in the Mexican economy by type of retailer, quantifying that spatial competition is an important determinant in explaining the differences in prices of tradeable merchandise between June 2009 and June 2018, a period of time characterized by low ERPT but high exchange rate volatility.

My estimates suggest that the ERPT into consumer prices in Mexico is on average low, but as it is a weighted average of the ERPT of the different retailer types, it is actually higher than the usual measured ERPT, which does not take the store type into account. I find that public markets, convenience and specialized stores in Mexico have a high ERPT; but that supermarkets and department stores have a significantly lower ERPT. High exchange rate volatility has been dampened by stores with high market shares. The total effect on welfare is, however, ambiguous, because, as Jia (2008) points out, it is possible that the current number of supermarkets allows the existence of a large number of convenience stores, which keep prices low but with a large ERPT. More supermarkets would imply fewer convenience stores, which has an ambiguous effect on the total level of ERPT but a positive effect on price levels.

While in this paper I take producer prices as exogenous, this analysis can be extended to Stackelberg games where multi-product (or any other dimension of non-zero market share) producers know how the retailers will flexibly mark up their prices and strategically set the producer prices to maximize profits. Also, the paper has something to say about the tradeoff between a scenario with higher but less volatile prices versus another one with lower but more volatile prices. In the international trade literature, higher but less volatile prices are associated with autarky, and lower but volatile prices are associated with international trade. The latter always dominates in terms of welfare, and for the case of this paper, the discussion would be analogous if large retailers and small retailers had the same marginal costs.

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Appendix

In order to separate the regressions that motivate the paper from the regressions that test the implications of the model and to avoid having to explain all the reduced form equations in the motivation, I have decided to write the former ones in this Appendix, since all the control variables have been explained already. To observe that ERPT varies by store type, the store fixed effects are now interacted with the exchange rate to obtain the marginal ERPT by store type. To simplify the analysis, I just let the retailer types to vary in one dimension: if they belong to a chain or not. The reduced form expression is

$$d\log p_{gr\tau\ell_t} = \left(\theta_j + \beta_{r\tau\ell}\right) \cdot d\log p_{j_t} + \alpha_t + \alpha_d + \alpha_g + \varepsilon_{gr\tau\ell_t} \tag{31}$$

and the average results (weighted by city population) are found in table 5, where it is possible to see that in general public markets and convenience stores pass through a larger share of the exchange rate onto their consumers, and in every case the store types that belonged to a chain had lower pass-through than the store types that did not belong to a chain.

Store Type	Chain	$\mathbb{E}_\ell[\beta_{r\tau\ell}]$
Specialized Store	Yes	2.37%
Supermarket	Yes	2.61%
Specialized Store	No	2.93%
Supermarket	No	3.37%
Department Store	Yes	3.61%
Convenience store	Yes	3.67%
Convenience store	No	5.15%
Public Market	No	8.61%

Table 5: Marginal ERPT by store type.

Note: The chain classification was done by the author. See section 5 for details on the criteria. The estimation is $d\log p_{g\tau\ell_t} = \beta_0 + (\theta + \beta_\tau) \cdot d\log e_t + \gamma X_t + \alpha_t + \alpha_d + \alpha_g + \varepsilon_{g\tau\ell_t}$ where $\log p_{g\tau\ell_t}$ is the percentage change in the price of generic product g in store type τ in city ℓ between the last time a product changed prices and date t, that a price change was observed; $\log e$ is the percentage change in the exchange rate for the same period of time. Price data from INEGI, cost-push data from Banco de México.

Since controlling by retailer type shows that the average ERPT in chains is lower, it becomes important to understand why this is the case. So I make use of the fact that I have the location of all the economic establishments in Mexico as well as all the people in Mexico from both the Economic and the Population censuses and construct the number of stores located at less than 1 kilometer away, to the average store of each store type. The results are in table 6. In this sense, the high volatility of the exchange rate has been good for competition and avoiding search frictions (like in Sorensen (2000)), and somehow the fact that these sectors were not competitive helped to observe low inflation even in the context of high depreciation. This does not imply that markups are small, which means that there still are potentially large price distortions in the tradeable merchandise market and larger gains from making not only supermarkets and department store sectors more competitive, but the rest of the retailer types as well. Other effects as well can be studied, like in Jia (2008), where the introduction of supermarkets reduced the number of convenience stores, affecting competitive margins across sectors.

Retailer Type	β_Supermarket	β_Specialized	β_Convenience	β_Department
Supermarket	0.00147	0.00113***	-7.59e-05**	0.0137***
Specialized Store	-0.0585	-0.00482	0.000262	0.0806
Convenience Store	-0.00444	-0.00701	7.73e-05	-0.00774
Department Store	0.00293	-0.00135**	-5.73e-05*	-0.00476

Note: Price, store location from INEGI, cost-push data from Banco de México. Pairwise distances elaborated by the author.

Table 6: Additional ERPT, as a function of the number of retailers less than 1km away. This measure varies at the city level since the data of the address of the stores is not available in this data set.

Mathematical Appendix

In this section I will derive the expressions for $\frac{\partial \log M_{r\tau\ell}}{\partial \log\left(\frac{p_{\tau\ell}}{p_{\ell}}\right)}$ and for $\frac{\partial \log M_{r\tau\ell}}{\partial \log\left(\frac{p_{r\tau\ell}}{p_{\tau\ell}}\right)}$, where $M_{r\tau\ell} = \frac{\varepsilon_{r\tau\ell}}{\varepsilon_{r\tau\ell}-1}$ and $\varepsilon_{r\tau\ell} = s_{r\tau\ell}\left(s_{\tau\ell} + (1-s_{\tau\ell})\,\sigma_T\right) + (1-s_{r\tau\ell})\,\sigma_R$. These two expressions are the most relevant theoretical contributions of the paper because they show that it is possible that retailers strategically decide not to pass-through onto consumers all of their input price changes via a flexible markup, and that the markup flexibility is proportional to the market share of the retailer.

$$
\begin{aligned}
\frac{\partial \log M_{r\tau\ell}}{\partial \log\left(\frac{p_{\tau\ell}}{p_\ell}\right)} &= \frac{\partial M_{r\tau\ell}}{\partial\left(\frac{p_{\tau\ell}}{p_\ell}\right)}\frac{\frac{p_{\tau\ell}}{p_\ell}}{M_{r\tau\ell}} = \underbrace{\left(\frac{\partial M_{r\tau\ell}}{\partial \varepsilon_{r\tau\ell}}\right)}_{A}\underbrace{\left(\frac{\partial \varepsilon_{r\tau\ell}}{\partial s_{\tau\ell}}\right)}_{B}\underbrace{\left(\frac{\partial s_{\tau\ell}}{\partial\left(\frac{p_{\tau\ell}}{p_\ell}\right)}\right)}_{C}\frac{\frac{p_{\tau\ell}}{p_\ell}}{M_{r\tau\ell}} \\
&= \underbrace{\left(-\frac{1}{(\varepsilon_{r\tau\ell}-1)^2}\right)}_{A}\underbrace{((1-\sigma_T)\,s_{r\tau\ell})}_{B}\underbrace{\left(\frac{(1-\sigma_T)\,s_{\tau\ell}}{\frac{p_{\tau\ell}}{p_\ell}}\right)}_{C}\frac{\frac{p_{\tau\ell}}{p_\ell}}{M_{r\tau\ell}} \\
&= -\frac{(1-\sigma_T)^2 s_{r\tau\ell}s_{\tau\ell}}{(\varepsilon_{r\tau\ell}-1)^2 M_{r\tau\ell}} \\
&= -\frac{(\sigma_T-1)^2 s_{r\tau\ell}s_{\tau\ell}}{(\varepsilon_{r\tau\ell}-1)\,\varepsilon_{r\tau\ell}}
\end{aligned}
$$

Analogously,

$$
\begin{aligned}
\frac{\partial \log M_{r\tau\ell}}{\partial \log\left(\frac{p_{r\tau\ell}}{p_{\tau\ell}}\right)} &= \frac{\partial M_{r\tau\ell}}{\partial\left(\frac{p_{r\tau\ell}}{p_{\tau\ell}}\right)}\frac{\frac{p_{r\tau\ell}}{p_{\tau\ell}}}{M_{r\tau\ell}} = \left(\frac{\partial M_{r\tau\ell}}{\partial \varepsilon_{r\tau\ell}}\right)\left(\frac{\partial \varepsilon_{r\tau\ell}}{\partial s_{r\tau\ell}}\right)\left(\frac{\partial s_{r\tau\ell}}{\partial\left(\frac{p_{r\tau\ell}}{p_{\tau\ell}}\right)}\right)\frac{\frac{p_{r\tau\ell}}{p_{\tau\ell}}}{M_{r\tau\ell}} \\
&= \left(-\frac{1}{(\varepsilon_{r\tau\ell}-1)^2}\right)(s_{\tau\ell}+(1-s_{\tau\ell})\,\sigma_T-\sigma_R)\left(\frac{(1-\sigma_R)\,s_{r\tau\ell}}{\frac{p_{r\tau\ell}}{p_{\tau\ell}}}\right)\frac{\frac{p_{r\tau\ell}}{p_{\tau\ell}}}{M_{r\tau\ell}} \\
&= -\frac{(\sigma_R-s_{\tau\ell}-(1-s_{\tau\ell})\,\sigma_T)\,(\sigma_R-1)\,s_{r\tau\ell}}{(\varepsilon_{r\tau\ell}-1)^2 M_{r\tau\ell}} \\
&= -\frac{(\sigma_R-1)\,s_{r\tau\ell}}{(\varepsilon_{r\tau\ell}-1)\,\varepsilon_{r\tau\ell}}\left(\sigma_R-(s_{\tau\ell}+(1-s_{\tau\ell})\,\sigma_T)\right)
\end{aligned}
$$

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