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

Fernando Pérez-Cervantes*

Banco de México

August 14, 2018

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 are more flexible when retailer market shares increase. This implies that the elasticities of the input price on final goods prices are estimated with attenuation bias when the store type is not used as a control in the estimation. There would be no attenuation bias if all retailers were measure zero or if preferences for store types were Cobb-Douglas. This means that the exchange rate pass-through (ERPT) is underestimated in most models that use micro data because some prices most likely are collected in non-measure zero stores and store types compete for market share. I then use all the price changes of tradeable merchandise in the Mexican Consumer Price Index (CPI) data between June 2009 and June 2018 as well as the changes in the USD/MXN exchange rate to test the model and find the ERPT underestimation. I am able to obtain the average ERPT levied onto consumers by the different types of retailers in Mexico. I find that prices in supermarkets and department stores are less volatile than public markets, convenience, and specialized stores. This is interpreted as higher elasticity of markups in the supermarket and department store sectors, which in turn implies those are more concentrated sectors than the rest. The ERPT by type of retailer is low for supermarkets and department stores, and positive or statistically not different from zero for the other types of retailers. I find that not taking into consideration the store type underestimates the ERPT by a statistically significant amount.

Keywords: Exchange Rate Pass-Through, Markups, Retailers

*fernando.perez@banxico.org.mx. This document was written as part of the 4th BIS-CCA Research Network Conference on Exchange Rates. The views expressed in this document are solely mine and do not reflect the view of Banco de México or its Board of Governors. I thank Alberto Ramírez de Aguilar and Stefano Molina for outstanding research assistance, Jim Tybout for the helpful comments, and Daniel Sámano for guidance and support.

1 Introduction

The recent long episode of constant depreciation of the Mexican peso against the U.S. dollar has lead policymakers to reanalyze the effect of the exchange rate on prices. Even though there is a vast and growing literature that has arrived to a consensus that for the case of Mexico, starting in 2002 the exchange rate pass-through (ERPT) has been low,[1/] there are growing concerns about the fact that these episodes of volatile exchange rates imply a larger volatility in prices.[2/] The immediate question arising from a sudden increase in volatility is if price volatility of all the goods increases by the same amount, and what can explain any differences, if any.

While seminal literature (see Burstein, Neves, and Rebelo (2003)) predicts that price changes coming from the exchange rate are lower for cities located away from the border, the evidence in Mexico shows, however, that this elasticity depends not only on the distance to the border, but on the type of store where products are sold. For this paper, I had access to the retailer names and their store types (convenience store, supermarket, department store, etc.) in the CPI micro data from INEGI and found that in Mexico price volatility is heterogeneous by store type.[3/] I did some tests to check whether incorporating this information to the usual analysis conducted by Central Banks could be enriched or even modified. I find that between 2009 and 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.[4/] In the same time period, informal markets were 1.6 times more volatile than supermarkets, while department stores were 0.9 times as volatile. The data shows that price changes that can be attributed to the exchange rate were much larger in Tijuana (a border city with the U.S.) than in Mexico City (900km away from the border), but marginally larger than San Luis Potosí (450km from the border).[5/] Adjusting by

[1/] See Chiquiar, Noriega, and Ramos-Francia (2010), Cortés Espada (2013), Aleem and Lahiani (2014), Peón and Brindis (2014), Baharumshah, Sirag, and Soon (2017), Kochen and Sámano (2016), Chávez and Alonso (2017), and Solorzano (2017) just to name a few examples.

[2/] The Bank of Mexico's quarterly report had an entire section studying exchange rate volatility, and the subject was mentioned in a number of speeches by the members of the Board.

[3/] To the best of my knowledge, this is the first time any published research has used this.

[4/] INEGI is the Spanish acronym of Instituto Nacional de Estadística y Geografía, the public institution in charge of statistical data in Mexico. One of their tasks is calculating inflation. Details on which products constitute tradeable merchandise for the purposes of this paper are in section 3.

[5/] Details of these calculations in section 4.

retailer type gives the usual result that Mexico City has significantly less ERPT than San Luis Potosí, which in turn has significantly less ERPT than Tijuana.

Using this evidence as motivation, I develop a structural model with nested CES preferences where the outermost nest is the store type to obtain optimal markups for heterogeneous multi product retailers when the prices of all their inputs are exogenous. 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. 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 markup. This implies that the elasticities of the input price on final goods prices are estimated with attenuation bias when the store type is not used as a control in the estimation (because averaging out by store type has zero mean). This Mexican evidence can immediately be contrasted with Cravino, Lan, and Levchenko (2018), where they find that 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, it is important to say 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.[6/]

In this paper, 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) and has access to the exogenous[7/] prices from the

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

[7/] This can be thought of as the producer not taking into consideration the location, type of store, or even name of the store to set prices.

producers of every generic product (for example, bottles of beer and dishwater soap) as well as exogenous input prices (wages, electricity, etc.). I build a model with nested CES preferences to obtain optimal markups for retailers and 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 their own retailer cannibalization effect is exactly offset with 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, Redding, and Weinstein (2016) from the producer point of view, and more recently studied by Eaton, Jinkins, Tybout, and Xu (2016) and Atkin, Faber, and Gonzalez-Navarro (2018) from the retailer point of view). My framework only uses CPI data and hence is widely applicable, because the CPI weights (given) allow to construct price indices of categories of products by city, and the CPI price observations allow to do this also by store type. Moreover, 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.

The model predicts that there are two dimensions along which markups vary between 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 is the market share of the retailer within the supermarkets), 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 is the share of supermarkets overall) depending if retailer within store types are better substitutes than store types or the other way around, respectively. The second dimension is in the elasticities of the markups. Higher markups are more flexible, meaning that 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. 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 shows that retailers set uniform markups by city, not uniform prices. Also, the uniform markups are set by city, not across the whole country because there are variations in the market share of the stores in the cities, even if the costs are identical for all cities. I test the model using CPI and Census data from Mexico. I find that department stores and supermarkets are the two most concentrated markets among store types of the CPI. As mentioned before, they also have the least volatile prices and higher markups.

The aim of this paper is to fit and enrich two rapidly growing areas in the literature. The first area is the one that studies flexible markups (see Burstein and Gopinath (2014) for an extensive literature review on this topic) by taking the producer prices as exogenous and adding the dimension that retailers have flexible markups. 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, Itskhoki, and Konings (2014), Auer and Schoenle (2016), and many others have pricing-to-market decisions and strategic complementarity which then retailers just levy onto consumers. This paper shows that the market share of the retailer is an important determinant of the markup. In fact, a non-negligible market share implies that the markups are flexible. There is substantial evidence that some retailers have large shares within their store types. While in this paper I study producer prices as being 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 markup their prices and strategically set the producer prices to maximize profits. Also, the paper has something to say about the trade-off 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. However,

The second area in the literature that this paper points at is the ERPT literature, where the consensus is that it is small (see Goldberg and Campa (2010) for a 21 industrialized economies study on the ERPT into the CPI, where they find that most of the ERPT comes from imported inputs of production and not imported final goods). I build a model where one of the implications is that if every retailer is zero-measure then the estimating equations collapse to the usual ERPT estimations. However, I find that if retailers are non-zero-measure then there is a correction term that has mean zero that acts like classic measurement error and thus biases downwards the estimates of the elasticities of the input prices on final prices. This means that the elasticity of the final price on exchange rates, or ERPT is most likely underestimated.

The paper is organized as follows. Section 2 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). Section 3 lists and explains the data sets used for estimation and briefly describes how the spatial competition measures were built and section 4 shows the different estimations of the ERPT conditional and unconditional on retailer information. Finally section 5 summarizes the results and concludes.

2 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 to 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 left the factory. The model is explicitly simple, and its main objective is to give loglinearized expressions for the data generating process of price changes, without an explicit model for internationally strategic producer decisions. The model allows 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 that there are flexible markups can potentially lead to underestimation of the ERPT.

It is 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). 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-Douglass such that the expenditure is constant and producers do not use their market power to affect aggregate spending.[8/] The model in this paper can be thought of as one of those, but where the first nest is Cobb-Douglass between tradeable merchandise goods and the rest of the goods in the economy, and in this paper I only care about the 3 remaining nests, where a constant fraction of the total expenditure is spent in the tradeable merchandise goods consumption bundle.[9/]

[8/] See Hottman, Redding, and Weinstein (2016) for an extensive analysis of this particular issue.

[9/] 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.

2.1 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 (in Mexico, one retailer in the convenience store type of store is *Oxxo*, and another one is *7-Eleven*). And once the retailer of each type of store is chosen, then 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 disjoint.

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 on 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.

So, given a set of generic products $G_{r\tau\ell}$ in retailer r of retailer type τ in location ℓ, 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:

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

where $\beta_{gr\tau\ell}$ is the preference parameter for generic good g and $\sigma_G > 1$ is the elasticity of substitution among generic products. The demand for generic g in retailer r of type τ in location ℓ 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 $p_{r\tau\ell} = \left(\sum_{g \in G_{r\tau\ell}} \beta_{gr\tau\ell} \left(p_{g\tau\ell}\right)^{1-\sigma_G}\right)^{\frac{1}{1-\sigma_G}}$ is the ideal price index for the consumer when shopping in retailer r of type τ. In the second stage, they take the price index of each retailer and decide how much to but 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.[10/] 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 in location ℓ of goods purchased in retailer r of type τ. The elasticity of substitution between retailers is $1 < \sigma_R < \sigma_G$ and the retailer amenity parameter is $\beta_{r\tau\ell}$. The demand products of retailer r of type τ in location ℓ 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 in retailer type τ. In the final stage, consumers combine all the bundles and derive utility from all the store types. The utility function is

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

where $q_{\tau\ell}$ measures the consumption in location ℓ of goods purchased in store type τ. The elasticity of substitution between store types is $1 < \sigma_T < \sigma_G$ 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

[10/] 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).

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 $p_\ell = \left(\sum_{\tau=1}^{T} \beta_{\tau\ell} \left(p_{\tau\ell} \right)^{1-\sigma_T} \right)^{\frac{1}{1-\sigma_T}}$ 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

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

Notice that nothing has been stated about the sign of $\sigma_R - \sigma_T$. This is not crucial to show that ERPT is underestimated because markups are flexible independent of the sign. I now briefly discuss the implications of different signs. Assume $p_{gr\tau\ell}$ to be unchanged. If $\sigma_R > \sigma_T$ then an increase in the price index of supermarkets makes 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

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

while the cross-price elasticity within store is

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

where $s_{gr\tau\ell}$ is the expenditure share in generic g conditional on buying in retailer r of type τ in location ℓ, $s_{r\tau\ell}$ is the share of expenditure in retailer r of type τ in location ℓ, and $s_{\tau\ell}$ is the expenditure share in store type τ in location ℓ. 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:

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

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

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

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

2.2 Retailers

Each period, the retailers of each type τ in location ℓ 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 in location ℓ buy all their generic goods $q_{ogr\tau\ell}$ from the producers (for example, a bottle of beer). For notation purposes, indexed with an o to separate it from when the generic product is bought by consumers), then add value added 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 $q_{igr\ell}$ are the purchases of input i (electricity, labor, etc.) and $q_{ogr\ell}$ are the purchases 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 value added. 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, what the retailer does is to compete 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 $m_{gr\tau\ell} = \frac{p_{gr\tau\ell} - c_{gr\tau\ell}}{p_{gr\tau\ell}}$ and, without loss of generality, assume $|G_{r\tau\ell}| = G$. 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 $\gamma = \sigma_G - s_{r\tau\ell}\left(s_{\tau\ell} + (1 - s_{\tau\ell})\,\sigma_T\right) - (1 - s_{r\tau\ell})\,\sigma_R$. 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 $\varepsilon_{r\tau\ell} = s_{r\tau\ell}\left(s_{\tau\ell} + (1 - s_{\tau\ell})\,\sigma_T\right) + (1 - s_{r\tau\ell})\,\sigma_R$.[11/] This generalizes the standard result (see Atkeson and Burstein (2008)) that within retailer cannibalization effect is exactly offset with between retailer substitution, which means 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.

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

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.

[11/] Proof: Let $A = \begin{pmatrix} -\sigma_G + \gamma s_{1r\tau\ell} & \cdots & \gamma s_{Gr\tau\ell} \\ \vdots & \ddots & \vdots \\ \gamma s_{1r\tau\ell} & \cdots & -\sigma_G + \gamma s_{Gr\tau\ell} \end{pmatrix}$. 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 $x = \frac{(1,1,...,1)^T}{\sigma_G - \gamma}$

2.3 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 on 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.

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-parametrized 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):

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

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.

2.4 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

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

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:

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

Using only prices and the CPI weights, 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

$$\frac{\partial \log M_{r\tau\ell}}{\partial \log\left(\frac{p_{\tau\ell}}{p_\ell}\right)} = -\frac{(\sigma_T - 1)^2 s_{r\tau\ell} s_{\tau\ell}}{(\varepsilon_{r\tau\ell} - 1)\,\varepsilon_{r\tau\ell}} \tag{23}$$

Notice that the markup would be inflexible to the retailer type relative price index if preferences were Cobb-Douglas for retail types. 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.

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

Also notice that this markup would be inflexible if preferences over retailers within store types was Cobb-Douglas. 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.

2.5 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

$$\begin{aligned} d \log p_{gr\tau\ell} &= d \log c_{gr\tau\ell} \\ &\quad - \frac{(\sigma_T - 1)^2 s_{r\tau\ell} s_{\tau\ell}}{(\varepsilon_{r\tau\ell} - 1)\, \varepsilon_{r\tau\ell}} d \log\left(\frac{p_{\tau\ell}}{p_\ell}\right) \\ &\quad - \frac{(\sigma_R - 1)\, s_{r\tau\ell}}{(\varepsilon_{r\tau\ell} - 1)\, \varepsilon_{r\tau\ell}} \left(\sigma_R - \left(s_{\tau\ell} + (1 - s_{\tau\ell})\, \sigma_T\right)\right) d \log\left(\frac{p_{r\tau\ell}}{p_{\tau\ell}}\right) \end{aligned} \tag{25}$$

So, using the price data to estimate the cost functions of the retailers but without correcting for the store type relative price (or controlling for store type) will downward 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, 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 elasticity of the markup is zero, meaning $d\log M_{r\tau\ell} = 0$ but most importantly all price changes can be mapped to marginal cost changes

$$d\log p_{gr\tau\ell} = d\log c_{gr\tau\ell} \tag{26}$$

Notice that equation 26 is the baseline expression for most of the ERPT estimation equations in recent literature (see Gopinath and Itskhoki (2010), Kochen and Sámano (2016), Baley, Kochen, and Sámano (2016), and Baharumshah, Sirag, and Soon (2017)). Suppose that $s_{r\tau\ell} = 0$ for every retailer and that you want to estimate the input price elasticities:

$$\begin{aligned} d\log p_{gr\tau\ell} &= d\log c_{gr\tau\ell} \\ &= s_{gr\tau\ell o} d\log p_{gr\tau\ell o} + s_{gr\tau\ell i}\cdot d\log p_{gr\tau\ell i} + \varepsilon_{gr\tau\ell} \\ &= \theta_{jgr\tau\ell}\cdot d\log p_{jr\tau\ell} + \varepsilon_{gr\tau\ell} \end{aligned} \tag{27}$$

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 25 I get

$$\begin{aligned} d\log p_{gr\tau\ell} = &-\frac{(\sigma_R - 1)\, s_{r\tau\ell}}{(\varepsilon_{r\tau\ell} - 1)\,\varepsilon_{r\tau\ell}} \left(\sigma_R - \left(s_{\tau\ell} + (1 - s_{\tau\ell})\,\sigma_T\right)\right) \underbrace{d\log\left(\frac{p_{r\tau\ell}}{p_{\tau\ell}}\right)}_{\text{mean zero}} \\ &+\theta_{jgr\tau\ell}\cdot d\log p_{jr\tau\ell} - \frac{(\sigma_T - 1)^2\, s_{r\tau\ell} s_{\tau\ell}}{(\varepsilon_{r\tau\ell} - 1)\,\varepsilon_{r\tau\ell}} \underbrace{d\log\left(\frac{p_{\tau\ell}}{p_{\ell}}\right)}_{\text{mean zero}} + \varepsilon_{gr\tau\ell} \end{aligned} \tag{28}$$

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 27 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 measurement error which implies that all the estimates of $\theta_{jgr\tau\ell}$ will be inconsistent and as the sample grows, converge to an attenuated value. The rest of this paper will stop being a discussion on flexible markups and only discuss the measurement error.

3 Data

In order to test this model I need to construct the time series of $p_\ell, p_{\tau\ell}, p_{r\tau\ell}, p_{gr\tau\ell}$. I also need time series of the input prices $p_{jr\tau\ell}$. To estimate costs, I will use the exchange rate and all the macroeconomic data for statistical *cost-push* analysis, which were obtained from Banco de México. The main sources of data is the CPI data from June 2009 to June 2018. There is a final exercise that uses producer data, in order to test some implications of the Hottman, Redding, and Weinstein (2016) model, and the producer data comes from IMPI, and it matches brand names with corporations and country of origin.[12/] I briefly describe the CPI data next.

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, 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.[13/] The Census of Population of 2010 indicates that the population of the 476 municipalities that constitute the 46 "cities" where the CPI data is collected add up to 85.4 million people, which was 75.67 percent of the population

[12/] IMPI is the Spanish acronym of Instituto Mexicano de la Propiedad Industrial, a public institution that promotes branding and fights piracy. One of their tasks is collecting and publishing data of every brand of product that is sold in Mexico.

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

and 88.06 percent of the total urban population of 2010. The same municipalities, using CONEVAL[14/] data for 2010, obtained 87.64 percent of the household income in Mexico.

Then, and 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 for 56.8 percent of the weight of the CPI. I take note of the product, the date (month) the price was collected, the city, and the type and name of the store where the product is sold.[15/] 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 remove all the observations that had product price change equal to zero. They are all reported.

It turns out that 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 set from INEGI shows 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).

[14/] CONEVAL is the Spanish 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.

[15/] 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.

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

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

The CPI has $T = 5$ store types in the data set: specialized store, convenience store, department store, informal market, 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. This, together with the generic expenditure shares, allows to have CPI weights at the generic-store type-city level. To the best of my knowledge, this had never been done before. Table 2 shows a summarized table of the data categories.

4 Estimation and Results

In this section I briefly describe the estimation equations to get the input price elasticities, including the ERPT. First, I start from a series of reduced form expressions where the store information becomes available 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

			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

Table 2: Descriptive statistics of the components of the CPI

equation 28 is

$$d\log p_{gr\tau\ell_t} = \theta_j \cdot d\log p_{j_t} + \alpha_t + \alpha_d + \alpha_g + \beta_{r\tau\ell} + \varepsilon_{gr\tau\ell_t} \tag{29}$$

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. These 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 depending 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 $d\log p_{gr\tau\ell_t} = 0$.

	(1)	(2)	(3)	(4)
Exchange Rate	0.285***	0.339***	0.319***	0.371***
	(0.038)	(0.04)	(0.037)	(0.043)
Electricity Prices	0.572***	0.582***	0.581***	0.671***
	(0.067)	(0.066)	(0.066)	(0.079)
IMF Commodities Index	-1.783***	-1.818***	-1.811***	-1.861***
	(0.197)	(0.195)	(0.195)	(0.232)
Formal Wages	2.36***	2.382***	2.37***	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***	-0.03***	-0.031***	-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	0.1208	0.1211	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 $h = 6\,months$

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

Then another exercise is done, where the store fixed effects are now interacted with the exchange rate. To simplify the analysis, I just let the retailers to vary in one dimension: if they belong to a chain or not.[16/] The reduced form expression is

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

and the average results (weighted by city population) are found in table 4, 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. This is interpreted as chains having larger market power, either for reasons that cannot be tested with the available data, like preference parameters or for other reasons that can be tested in further work, like lower prices of the same products in the same city, or less increases in their marginal costs.

Store Type	Chain	$\mathbb{E}_\ell[\beta_{r\tau\ell}]$
Price Club	Yes	2.09%
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 4: Average additional ERPT by store type, where the store type is interacted with the exchange rate.

4.1 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.[17/] The

[16/] 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.
[17/] I am implicitly assuming that the retailers within a store type that do not belong to a chain have zero market share.

model predicts that if there are no controls for store type, the ERPT is larger in those firms (because it is estimated without measurement error), 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 29 and the results are in table 5. The results suggest that the model is correct 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.

	(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

*** 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 $h = 6\, months$

Table 5: 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

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, and how much of the measurement error. 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, Redding, and Weinstein (2016) have documented that there is quite significant variation in the ERPT to the retailers depending on the producer share of the market. Some products have specifically no brand, being agricultural products 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 wasn't 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.

4.2 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 the figure 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 measurement error when calculating the pass-through, but in the short run it is always the case

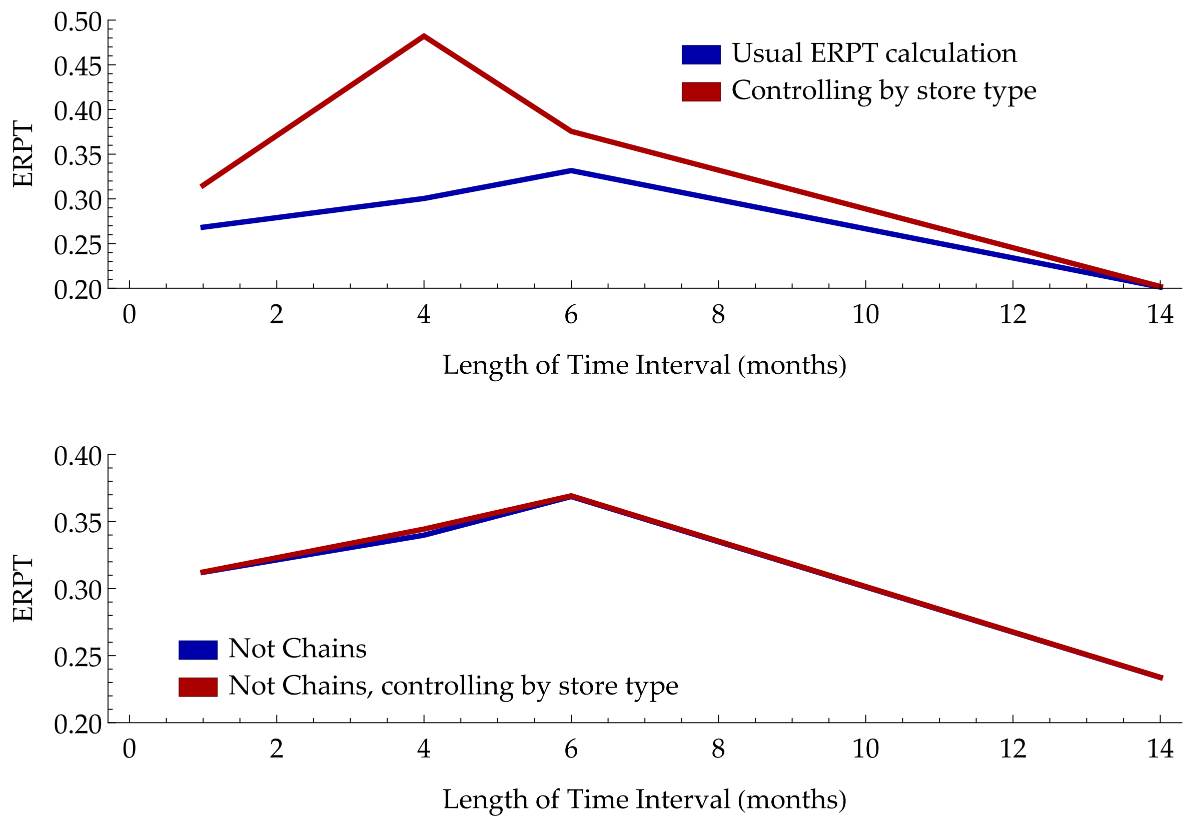

Figure 1: ERPT when changing the length of the time interval

that ERPT is lower when the estimation does not take into account the store type. 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.

4.3 Variable markups by spatial competition (advanced measures)

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

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.

5 Summary of the Results and Conclusion

The section above allows to clearly see that the ERPT is underestimated when the store type is not included in the estimation. Not even the generic product fixed effects can change this result. The average ERPT is almost not affected when adding city controls and for the products. This result holds controlling by CPI city too. This implies that there must be something going on at the retail level that varies a lot by city and by (observed) product. This turns out to be the store types market share distribution, and in particular supermarkets and department stores seem to have a small amount of big dominant players that dampen the ERPT. 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 by and quantifies that the spatial competition is an important determinant to explain the differences in prices of tradeable merchandise between June 2009 and June 2018, a period of time characterized by low ERPT but with high volatility in the exchange rate.

My estimates suggest that the ERPT into consumer prices in Mexico is on average low because it is a weighted average of the ERPT of the different retailer types. I find that public markets, convenience and specialized stores in Mexico have a high ERPT; supermarkets and department stores have a significantly lower ERPT. Averaging out these coefficients gives the usual low ERPT. The high volatility of the exchange rate has been good for competition. The total effect is, however, ambiguous, because, as Jia (2008) points out, it is possible that the current number of supermarkets allows the existence of a large amount of convenience stores which keep prices low but with a large ERPT. More supermarkets would imply less convenience stores, which has ambiguous effect on the total level of ERPT but a positive effect on price levels.

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