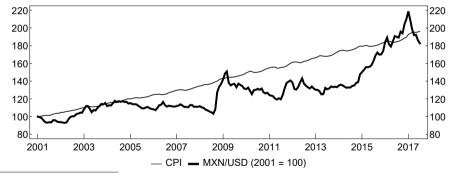


- Influential literature that studies producer pricing using retailer prices.
 - √ Flexible markups: Gopinath and Itskhoki (2010), Burstein and Gopinath (2014), Amiti, Itskhoki, and Konings (2014), Hottman, Redding, and Weinstein (2016)
- Assumes that reailers pass onto consumers all the producer pricing via an inflexible markup.
- There is a fast-growing literature that studies retailer pricing.
 - √ DellaVigna and Gentzkow (2017) show that it is suboptimal that department stores, pharmacies and food stores impose (almost) uniform pricing across locations.
 - ✓ Cravino et al. (2018) 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.

Mexico:

- Argente, Hsieh and Lee (2017) show, using Nielsen data, that in Mexican urban areas rich households buy the same products for an average 3% higher prices than poor households.
- Atkin et al. (2018) estimate the welfare gains of adding more retailers to the market.

- In recent years, the peso/dollar exchange rate has increased its volatility, reviving the policy analysis of its impact on consumer prices.
- There is consensus that since 2002 the exchange rate pass-through in Mexico (ERPT) is low in the short and medium run. 1/



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 Solórzano (2017) just to name a few examples.

- ERPT papers written for Mexico are on the "producer pricing using retailer prices" literature.
 - √ In fact, most studies with micro data in every country have similar assumptions.
- Then I found out why....
- I tried to "replicate" the Argente et al. (2017) result but with 100% of the CPI instead of with Nielsen data (around 1/3 of the CPI components) and with the demographics of the store location instead of household data.
 - √ I was not granted the addresses of the stores.
 - ✓ It turns out this information is extremely sensitive for the Bank.
 - > May be the reason why other countries also do not exploit retailer types?
- It is not obvious that the store information will enrich the empirical analysis of the ERPT
 - ✓ If the stores change all the time in the CPI data, then there is no price change data.
 - ✓ Inflexible markups, even if they are different by retailer type have zero effect on the ERPT estimation.
 - ✓ If similar retailers take similar decisions but the decisions differ by city, then it may well be about preference parameters, which are almost impossible to estimate using price data.

- I was granted all the CPI microdata, with store type and the store names.
 - √ I later found out it was the first time ever this had happened for research purposes.
 - √ All monthly prices from June 2009 to March 2018.
- Research Question: Does the data show that different retailers price differently their goods?
 - √ What does "different" even mean?
 - Do convenience stores and supermarkets in the same city price differently the same can of soda?
 - Do chains price differently than non-chains?
 - Does the same supermarket chain price differently in Mexico City than in Tijuana?
- Research Question: Does controlling for retailer type affect the ERPT results?
 - √ Is there any obvious trend that can be found in the data that differs by store type?
 - √ What are the possible explanations for this?

First dive in the data

- As part of their constitutional task of measuring inflation in Mexico, INEGI's methodology to collect prices involves observing comparable products over time.^{2/}
- 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.
 - ✓ INEGI collects the data of the name of the store and the type of store.
- The Consumer Price Index (CPI) data set from INEGI shows that between June of 2009 and March of 2018 the average product-store combination of consecutive price observations was 36 months.

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.

Doing a simple regression of ERPT

$$d \log p_{g\tau\ell_t} = \beta_0 + (\theta + \beta_\tau) \cdot d \log e_t + \gamma X_t + \alpha_t + \alpha_d + \alpha_g + \varepsilon_{g\tau\ell_t}$$

yields that there is a significant difference in the ERPT level by store type.

| Store Type | Chain | $eta_{	au}$ |
|-------------------|-------|-------------|
| 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% |

Aim of this paper

- To write a model that is not far away from the standard literature, but with the slight modification of consumers having preferences for the store type.
 - √ The chosen literature is Atkeson-Burstein-Gopinath-Itskhoki (and recently Eaton-Tybout)
- Ideally, this model has, as an equilibrium object, similar price levels over time, but different price volatilities by type of store.
 - √ Hopefully something to say about chains vs. not chains.
 - √ Then I can test whether the differences in price volatilities affect ERPT (or any other) calculations.

Preview of the results

- The model predicts that markups are increasingly flexible in store type market shares.
- The markup is the same for every product sold in the same store and it does not depend on the elasticity of substitution between goods in the store (similar to Atkeson-Burstein result).
 - ✓ Special case: stores with zero market share have positive but inflexible markups that <u>depend only</u> on the elasticity of substitution between stores (exactly the Atkeson-Burstein result).
 - √ Corolary: producer pricing models that use retail prices map directly if all stores have zero market share.
- The markup flexibility has a negative coefficient, so price volatility is lower in concentrated store type markets.
 - √ The usual Exchange Rate Pass-Through (ERPT) estimation equation should be corrected and be controlled by store type, because otherwise is estimated with attenuation bias due to classic measurement error.
- CONTEXT: This is an important at least in Mexico since the recent literature mentions that ERPT is low, while some of our store types are very concentrated markets.

Roadmap

1. Model Structure and Identification Strategy

2. Results

Model

- Consumers: nested CES demand structure.
 - ✓ Consumers in each location (indexed with ℓ , and in the data locations are cities) have preferences over a fixed set types of stores (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).
- **Retailers**: single plant firms (i.e. make decisions in only one location).
 - ✓ Generic products are purchased by retailers 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.

Equilibrium Objects

Consumers

■ The demand for any generic *g* in terms of generic prices, retail price indices, retailer type price indices, location level price indices and expenditure is

$$q_{gr au\ell} = eta_{gr au\ell}eta_{r au\ell}eta_{r\ell}\left(p_{gr au\ell}
ight)^{-\sigma_G}\left(p_{r au\ell}
ight)^{\sigma_G-\sigma_R}\left(p_{ au\ell}
ight)^{\sigma_R-\sigma_T}\left(p_\ell
ight)^{\sigma_T-1} extstyle E_\ell$$

Retailers

■ The cost of producing one unit of generic good g by retailer r of type τ is

$$c_{gr au\ell} = \left(\sum_{i \in I_{gr au\ell}}
u_{gr au\ell i} \left(
ho_{gr au\ell i}
ight)^{1-\eta} +
u_{gr au\ell o} \left(
ho_{gr au\ell o}
ight)^{1-\eta}
ight)^{rac{1}{1-\eta}}$$

- They face a perceived elasticity of $\varepsilon_{r\tau\ell} = s_{r\tau\ell} \left(s_{\tau\ell} + (1 s_{\tau\ell}) \, \sigma_T \right) + (1 s_{r\tau\ell}) \, \sigma_R$
- The markup is the same for every product they sell

$$M_{gr au\ell} = rac{
ho_{gr au\ell}}{c_{gr au\ell}} = M_{r au\ell} = rac{arepsilon_{r au\ell}}{arepsilon_{r au\ell} - 1}$$



Comparative Statics

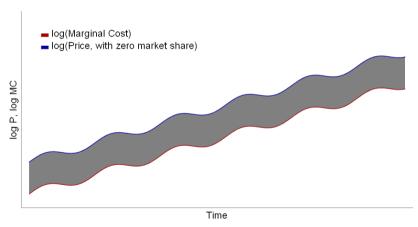
- The model derives a set of predictions that can be tested in the data. In this paper I will assume that $\nu_{qr\tau\ell i}$, $\beta_{qr\tau\ell}$, $\beta_{rr\ell}$, $\beta_{\tau\ell}$, σ_G , σ_R , σ_T , η are constant over time.
 - √ This means that in equilibrium the only sources of variation of market shares, markups, etc. are the input prices in the retail production function of generic final goods and the number of products that each retailer sells.
- The model predicts that the elasticity of the markup with respect to the store type relative price with respect to other types of stores $\frac{p_{\tau\ell}}{p_e}$ is negative

$$\frac{d\log M_{r_{\tau\ell}}}{d\log\left(\frac{p_{\tau\ell}}{p_{\ell}}\right)} = -\frac{\left(\sigma_{T} - 1\right)^{2} s_{r_{\tau\ell}} s_{\tau\ell}}{\left(\varepsilon_{r_{\tau\ell}} - 1\right) \varepsilon_{r_{\tau\ell}}}$$

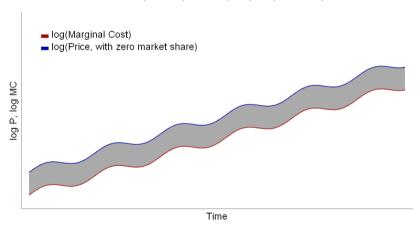
The model predicts that the elasticity of the markup with respect to their own price index relative to the same store type price index $\frac{p_{r\tau\ell}}{p_{r\ell}}$ is

$$rac{d\log M_{r au\ell}}{d\log\left(rac{
ho_{r au\ell}}{
ho_{ au\ell}}
ight)} = -rac{\left(\sigma_R - 1
ight)s_{r au\ell}}{\left(arepsilon_{r au\ell} - 1
ight)arepsilon_{r au\ell}}\left(\sigma_R - \left(s_{ au\ell} + \left(1 - s_{ au\ell}
ight)\sigma_T
ight)
ight)$$

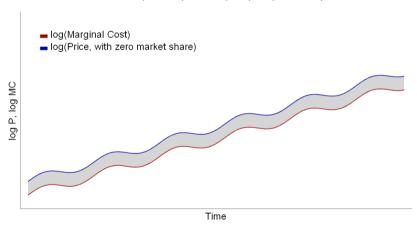
$$\varepsilon_{r\tau\ell} = \mathbf{s}_{r\tau\ell} \left(\mathbf{s}_{\tau\ell} + (1 - \mathbf{s}_{\tau\ell}) \, \sigma_T \right) + (1 - \mathbf{s}_{r\tau\ell}) \, \sigma_R$$



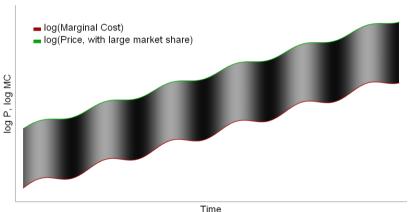
$$\varepsilon_{r au\ell} = s_{r au\ell} \left(s_{ au\ell} + (1 - s_{ au\ell}) \, \sigma_T \right) + (1 - s_{r au\ell}) \, \sigma_R$$



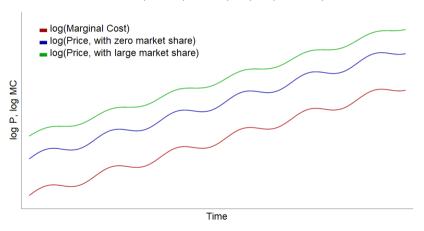
$$\varepsilon_{r au\ell} = s_{r au\ell} \left(s_{ au\ell} + (1 - s_{ au\ell}) \, \sigma_T \right) + (1 - s_{r au\ell}) \, \sigma_R$$



$$\varepsilon_{r\tau\ell} = \mathbf{s}_{r\tau\ell} \left(\mathbf{s}_{\tau\ell} + (1 - \mathbf{s}_{\tau\ell}) \, \sigma_T \right) + (1 - \mathbf{s}_{r\tau\ell}) \, \sigma_R$$



$$arepsilon_{r au\ell} = \mathbf{s}_{r au\ell} \left(\mathbf{s}_{ au\ell} + (\mathbf{1} - \mathbf{s}_{ au\ell}) \, \sigma_T \right) + (\mathbf{1} - \mathbf{s}_{r au\ell}) \, \sigma_R$$



- The model predicts that the markups are flexible when the retailer market share is large.
 - ✓ Since the coefficient is negative, this implies that the price volatility of concentrated retail type sectors is lower than the one in more granular sectors.
- On average, the prices of the same generic goods, sold in different store types but in the same city, should grow at similar rates.
- Complementarity? Absorbing state? It seems to be for increases in marginal costs. The opposite for decreases in marginal costs. Assume a shock that affects the marginal costs of every store within a store type.

large market share o less volatility o less growth in price index o more market share

Identification strategy

The model implies that if prices are flexible and their only source of variation is input prices. then the expression can be rearranged to

$$d \log M_{gr\tau\ell} = d \log p_{gr\tau\ell} - d \log c_{gr\tau\ell}$$

$$= -\frac{(\sigma_T - 1)^2 s_{r\tau\ell} s_{\tau\ell}}{(\varepsilon_{r\tau\ell} - 1) \varepsilon_{r\tau\ell}} d \log \left(\frac{p_{\tau\ell}}{p_{\ell}}\right)$$

$$-\frac{(\sigma_R - 1) s_{r\tau\ell}}{(\varepsilon_{r\tau\ell} - 1) \varepsilon_{r\tau\ell}} (\sigma_R - (s_{\tau\ell} + (1 - s_{\tau\ell}) \sigma_T)) d \log \left(\frac{p_{r\tau\ell}}{p_{\tau\ell}}\right)$$

Identification strategy:

$$d \log p_{gr au\ell} = d \log c_{gr au\ell} + eta_{ au\ell} d \log \left(rac{oldsymbol{p}_{ au\ell}}{oldsymbol{p}_{\ell}}
ight) + eta_{r au\ell} d \log \left(rac{oldsymbol{p}_{r au\ell}}{oldsymbol{p}_{ au\ell}}
ight)$$

Identification strategy of the ERPT

■ The usual ERPT estimation equations, where one of the input prices of the generic products is the exchange rate, assumes that the errors are mean zero.

$$d\log p_{g\ell} = \sum_i s_{g\ell i} d\log p_{g\ell i} + \underbrace{arepsilon_{g\ell}}_{\mathsf{mean zero}}$$

However, estimation the expression of the model, controlling only by input prices also has mean zero, because if prices change at different rates in different store types, they exactly cancel each other out as you vary store types.

$$d\log p_{gr\tau\ell} = \sum_{i} s_{gr\tau\ell i} d\log p_{gr\tau\ell i} + \beta_{\tau\ell} \underbrace{d\log \left(\frac{p_{\tau\ell}}{p_{\ell}}\right)}_{\text{mean zero}} + \beta_{r\tau\ell} \underbrace{d\log \left(\frac{p_{r\tau\ell}}{p_{\tau\ell}}\right)}_{\text{mean zero}} + \underbrace{\varepsilon_{gr\tau\ell}}_{\text{mean zero}}$$

■ This is the classic measurement error! All the coefficients $s_{gr\tau\ell i}$ will be underestimated in absolute value as long as the prices collected in the CPI micro data are collected in stores with positive market share.

Roadmap

1. Model Structure and Identification Strategy

2. Results

Results

■ Estimating the ERPT. Controlling for store type increases the ERPT by around 10 percent.

| | (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 | | \checkmark | | ✓ |
| 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



Results

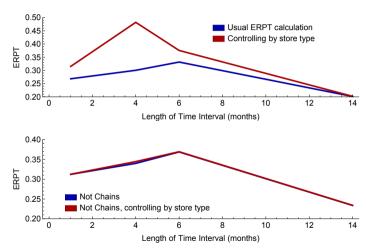
Using infinitesimal stores (not chains) results in a higher estimate of the ERPT, and one that is very close to the one with the whole sample and controlling for store type.

| | (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

Results

Estimating the ERPT



Concluding Remarks

- It turns out that having the store type data is important.
 - √ Different store types price differently, and it seems that even the ERPT is different
- A simple model shows that one mechanism that explains differentiated ERPT is that markups are flexible for stores with a large share of the market.
 - √ The larger the share, the higher the markup and the lower the volatility of prices.
- Estimating the model shows that ignoring the store types leads to classic measurement error, thus attenuated coefficients for input price elasticities.
 - √ This means that the ERPT is underestimated.
- The model is tested and it confirms that ERPT is underestimated.

