Price Age and Exchange Rate Pass-Through*

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Abstract

We document a negative relationship between the age of a item's price –the duration of a price between price changes– and exchange rate pass-through. Using non-public price micro data from the Mexican CPI, we find that exchange rate pass-through is higher when prices are younger (recently changed) than when price are old. Specifically, exchange-rate passthrough is 50% smaller for six-month old prices compared to one-month old prices. We provide further evidence of the negative relationship between age and pass-through using an exogenous natural experiment. In January of 2014, there was an unexpected change in the value added tax for a variety of products in Mexico that forced many prices to change and thus become young. We find that exchange-rate pass-through is larger during the six months window after the VAT shock compared to the six months previous to the shock. The evidence documented in this paper supports models of price-setting behaviour with age dependence.

JEL classifications: E31, F31, F41.
Keywords: Micro Price Data, Nominal Stickiness, Exchange Rate Pass-Through.

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1 Introduction

We document a negative relationship between the age of a item's price– the duration of a price between price changes – and exchange rate pass-through (ERPT). Using non-public item-level price quotes from the Mexican CPI, we find that exchange rate pass-through is higher when its price is young than when its price is old. For this purpose, we follow the methodology in Berger and Vavra (2015) who build on previous work by Gopinath and Rigobon (2008), Gopinath, Itskhoki, and Rigobon (2010), Gopinath and Itskhoki (2010), and construct measures of cumulative exchange rate depreciation between price changes and then estimate passthrough as the coefficient from an OLS regression using the size of price change as endogenous variable. Specifically, in our preferred specification, exchange rate pass-through is 50% lower for prices that are six-months old compared to prices that are only one-month old.

We provide further evidence of the negative relationship between age and pass-through using a natural experiment. In January of 2014, there was an unexpected change in value added tax for a variety of products, that forced many prices to change (and thus become young). We find that exchange-rate pass-through is larger during the six months window after the VAT shock compared to the six months previous to the shock. This evidence supports models of price-setting behaviour with age dependence.

This paper complemennts literature that analyzes the ERPT to prices using micro data. For example, Gopinath and Rigobon (2008) use micro data underlying the US import and export price indexes to document different facts about the degree of price stickiness across borders. They also present an estimation of the ERPT into import prices using this micro data. Other papers have analyzed the relation between the frequency of price change and the ERPT (Gopinath and Itskhoki, 2010) and the relation between the choice of currency of imports and the ERPT (Gopinath, Itskhoki, and Rigobon, 2010). Burstein and Gopinath (2014) present a survey of the empirical and theoretical literature of exchange rate and prices. Berger and Vavra (2015) show that there exists a relation between volatility and exchange rate pass-through using import price micro data from the US. For Mexico, only Kochen and Sámano (2015) have used price micro data to analyze the ERPT in Mexico.

Our paper is closely related to the pricing literature, particularly to models that generate age dependence in pricing decisions. Baley and Blanco (2015) develop a model of pricing with menu costs and information frictions, where firms learn their permanent level of productivity. Uncertainty surrounding the forecasts affects the size of price changes and the frequency of adjustment. Firms with more uncertain forecasts change their prices more often and for a larger amount than firms with more certain forecast. As firms' uncertainty about productivity decreases with the age of a price, price age is a determinant of the size and frequency of adjustment. Such a model generates a decreasing hazard rate of price adjustment. These predictions are documented empirically by Campbell and Eden (2014) using weekly scanner data. They find that young prices (set less than three weeks ago) are relatively more dispersed and more likely to be reset than older prices. Our results on age dependence are in line with those in Carvalho and Schwartzman (2015) who show that in time-dependent sticky price models, monetary non-neutrality is larger if older prices are disproportionately less likely to change.

2 Data

We use non-public micro data of product level price quotes underlying the Mexican CPI, the *Índice Nacional de Precios al Consumidor* (INPC). Data frequency is biweekly and for some products, such as food, is weekly. However, we use monthly observations for the main analysis since the exchange rate is too volatile at higher frequencies.[1]

The micro data identifies products at a detailed level. Each price quote has information about the product's brand, product's description, and an outlet unique identification number (e.g. Bottled refreshment, brand Coca-Cola, non-returnable, bottle of 3 liters, sold in outlet 31272 in Mexico City). In addition, the data set contains information about the price collection. In particular, it specifies if the product was on sale or was missing when the price was quoted.[2] There is also a product substitution indicator and the reason why it was substituted.[3] Given the detail of the data set we are able to properly address for the presence of sales and product substitutions, features that have proved to be relevant for the price-setting empirical analysis using CPI micro data (Nakamura and Steinsson, 2008).

The goods and services are classified into three aggregation levels: (1) item's variety, (2) the city of quotation, and (3) generic item categories. Generic item classifications are broad consumption categories used to group individual products, for example, "Bottled refreshments" or "Haircuts". These categories are analogous to the Entry Level Items of the US CPI. Item's varieties apply for some generic items with further disaggregated classifications. The expenditure weights that are used for the empirical analysis are specific to the variety-city-generic level.[4] For further details about the data see Kochen (2015).

2.1 Sample

The sample covers the period from June 2009 to December 2015. In terms of CPI basket coverage, we restrict to 212 out of 283 generic items. All-together these items represent 41.5% of the Mexican CPI basked, measured by household expenditure weights. Since the goal is to analyze the response of prices to exchange rate shocks we restrict to the goods that could be classified as tradables. The sample selection of the generic items considered for the empirical analysis is as follows.

First, we drop the 46 CPI services that represent 43.1% of the CPI. The main generic items excluded are shelter, food services and education. Second, we exclude the items whose price is regulated or is given by government approved fares since their price dynamics reflect administrative considerations rather than those of the market. Examples of these items are gasoline and public services, such as public transportation or water supply. Overall, a total of 14 items, with a total expenditure weight of 14.1%, are excluded for this reason. Additionally, 11 items with a total weight of 1.3% were excluded. From these, 5 generic items, with a total weight 0.17%, were excluded because of missing data before the CPI basket revision

[1]From the CPI micro data we construct monthly prices considering the last weekly or biweekly price quote of each month. We check the robustness at different frequencies in Section 3.

[2]Sales are define as all the non-conditional price discounts in terms of a minimum number of products bought or a determined form of payment.

[3]A product could be substituted because of the following reasons: a permanent product shortages, the closure of the source where the item was quoted, new product incorporation, the change in the product presentation, or the change in the type of the service provided.

[4]The weights used in the INPC are derived from the Survey of Household's Income and Expenditures, *Encuesta Nacional de Ingreso y Gasto de los Hogares* (ENIGH). This ensures that the INPC generic item categories covers more than 95% of Mexican household's expenditures (INEGI, 2013).

of December 2010.[5] Furthermore, 3 items, with a weight of 0.38% were excluded because of its price collection procedures which difficult the empirical analysis.[6] Finally, 4 unprocessed food items, with a total weight of 0.7%, were excluded because of their high frequency of price change.

2.2 Sales, product substitutions, missing values and small price changes

The micro data used in this paper has some important advantages over the data sets used in previous empirical studies for Mexico. For example, Gagnon (2009) use monthly average prices (of the two or four prices of each month) of the CPI product-level price quotes that are published in the Mexican government's official gazette, the *Diario Oficial de la Federación* (DOF). The use of average prices, instead of the direct price quotes, complicates the inference since the price changes of average prices will be smaller and more frequent generating biases in the price-setting calculations.[7] Additionally, the DOF data set does not report any additional information about the price collection, in particular about the presence of sales or missing values.

Sale-related price changes and stock-outs are two relevant features of the CPI micro data that have to be addressed for an accurate analysis of the price-setting and exchange rate pass-through. In particular, sales have become relatively more frequent in recent years in Mexico: the monthly percentage of sales, with respect to the total number of price quotes, has almost doubled from 4% in 2009 to a level of 8% in 2015. Given this, we follow the price-setting empirical literature and distinguish between two classes of price changes: (1) posted prices, and (2) regular prices which filter out sale-related price changes. For this paper, we identify sale-related price changes using the sale flag reported in the micro data. To address for the presence of sales and stockouts we construct posted and regular "latent" prices. Posted latent prices carry forward the last observed posted price through stockout periods, while regular prices carry forward the last observed regular price during both sales and stockouts. For our empirical results we carry forward the latent prices during a maximum of 5 months. If there is no observed posted or regular price after this time period we do not consider these observations.[8]

To minimize the presence of measurement errors, for example due to uncontrolled quality changes, we discarded the price changes related with product substitutions. Additionally, we address for possible spurious small price changes in the data.[9] One important source of spurious small price changes in the Mexican CPI micro data is the practice of unit measure prices (e.g. price per kilogram). For 110 of the 212 in-sample generic items, the prices are captured in a common unit size. For these items whenever

[5] In December 2010 there was a major basket revision that resulted in a reduction of the generic item categories, from 315 to the current number of 283: 8 generics were open in 20 new generic items, 70 were merged in 29 items and 3 were eliminated. For further details of the 2010 basket revision see INEGI (2013).

[6] Two items whose prices require specific treatments for inflation measurement were excluded. This type of items have certain characteristics that require particular price collection procedures (INEGI, 2013). This type of goods are analogous to the composite-good items of the US CPI. Eichembaum et al (2014) show that considering the prices of this type of items could cause a large share of spurious small price changes. Additionally, we the generic item watches, jewelry and costume jewelry is excluded because their price variation before the 2010 basket revision was imputed from gold and silver prices.

[7] For a further discussion about the implications of the use of average prices for the price-setting analysis see Gagnon (2009). To address for the averaging of the prices, a filter is employed in that paper to estimate monthly price statistics with the DOF micro data.

[8] The construction of latent prices will be particularly important in the pass-through analysis since we calculate the cumulative change of the exogenous variables over the course of price spells. Left and right censoring in spells, i.e. cases of unobserved beginning or ending of the price, will affect the construction of these variables. The use of latent prices, compared to the use of contiguous prices only, considerably reduces the number of censored spells in the data.

[9] Eichembaum et al (2014) shows that spurious small price changes are frequent in the US CPI micro data.

a product has a different size the posted price is converted to the common unit (INEGI, 2013). As a consequence of this reporting practice spurious small price changes are likely to occur. To address for this particular measurement problem we follow Kochen (2015) and use a conversion factor reported in the data, that was used to calculate the unit size price, to reconstruct posted prices.

2.3 Price Age

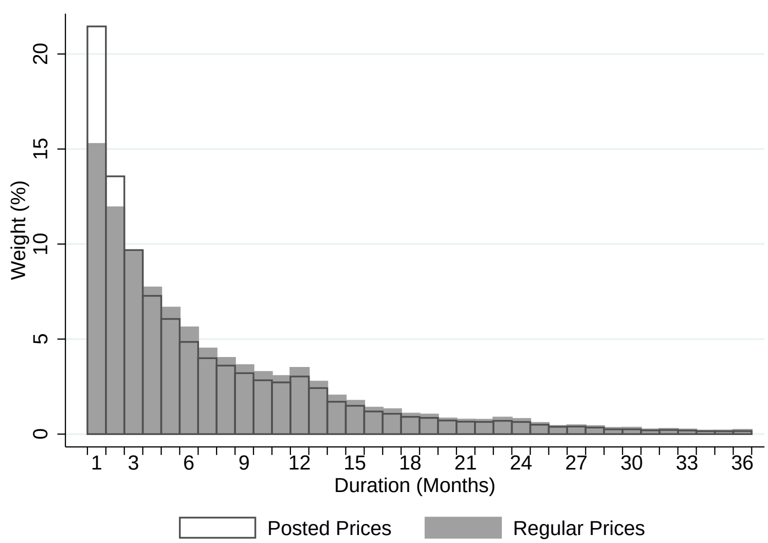
The key variable in our study is price age. For each specific product s, we compute the age of the price at time t, age_t^s, as the difference between t and the date of the last price change τ.

$$age_t^s \equiv t - \tau_s, \qquad \text{with} \qquad \tau_s = \quad \max\{r \leq t : \quad p_r^s \neq p_t^s \quad\}$$

Price age is a measure of time-varying duration at the product level. We define price duration as the complete length of the price spell. For example a price that is unchanged through 5 months had an age of 1, 2, ..., 5 months before the change.

Figure I presents the distribution of uncensored price spells in the data, for both posted and regular prices.[10] Posted prices have a lower duration than regular prices at all maturities.

Figure I: Price Duration (Months)



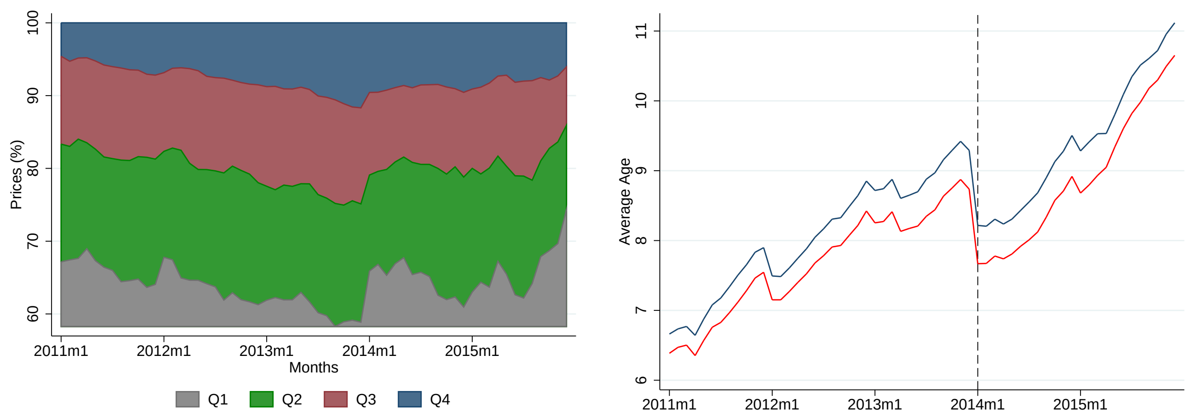
[10]A well-known disadvantage of calculating the duration of prices directly from the data is spell censoring, i.e. that the beginning or the end of the price is not observed. Spell censoring could bias the duration downwards since large spells are the ones more frequently affected by censoring. We have conducted several robustness checks regarding censoring and conclude that there is no significant change in our results if we include or exclude left or right censored spells.

2.4 Descriptive statistics

Cross-sectional properties of price age Here we show micro-price statistics conditional on price age: average size and dispersion of price changes and average frequency of price changes for young and old prices.

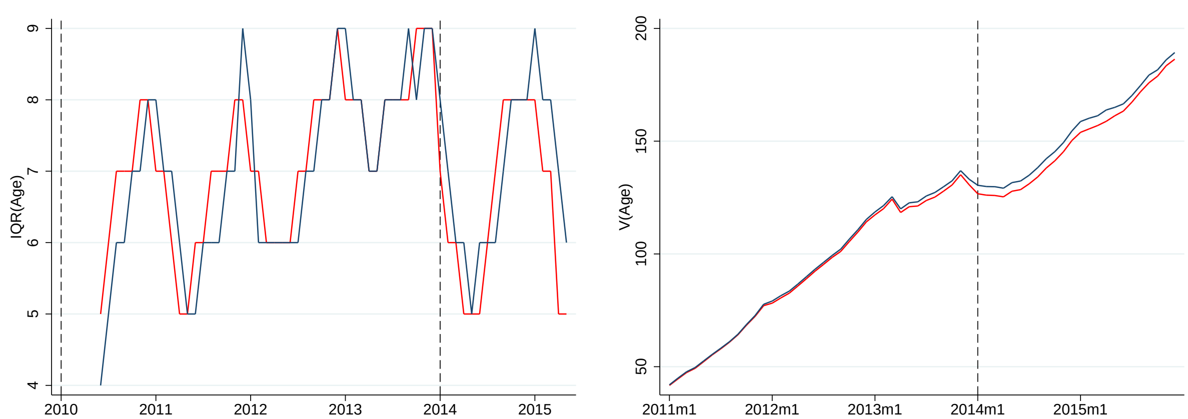
Time-series properties of price age To describe the evolution of price age across time, we show the distribution of prices considering the duration quartiles in the sample (left) as well as the mean age (right). The left figure shows the impact of the January 2014 VAT change on the average price age. The figures clearly show the sharp drop in average age in January of 2014 as a result of the change in value added and other taxes that gives rise to the natural experiment discussed in Section 6.

Figure II: Evolution of Price Age



As measures of dispersion of price age, we show the evolution of the interquartile range (left) and variance (right) of the price age distribution.

Figure III: Interquartile Range and Cross-sectionalVariance of Price Age



Price age and business cycle Plot this against business cycle.

3 Price Age and Pass-Through

3.1 MRPT

We base our empirical analysis in a specification called medium-run pass-through (MRPT) which is as follows. Let $\Delta p^R_{s,t}$ be product s's log price change at time t relative to the aggregate inflation before the adjustment and let $\Delta_c RER_{s,t}$ refers to the cumulative change in the log peso-US dollar real exchange rate, computed as the difference between the cumulative change in the nominal exchange rate and the cumulative inflation differentials:

$$\begin{aligned} \Delta p^R_{s,t} &\equiv \Delta p_{s,t} - \Delta_c P_{s,t} \\ \Delta_c \mathrm{RER}_{s,t} &\equiv \Delta_c \mathrm{NER}_{s,t} + \Delta_c P^{\mathrm{US}}_{s,t} - \Delta_c P_{s,t} \end{aligned}$$

Let X^s_t be vector of control variables, which we describe in detail below. ERPT into consumer prices is estimated using the following regression for all non-zero price changes in real terms:[11]

$$\Delta p^R_{s,t} = \beta \Delta_c \mathrm{RER}_{s,t} + \gamma' X^s_t + \epsilon^s_t \tag{1}$$

Since our main interest is to analyze the relation between prices' age and ERPT we consider the specification in real terms as our baseline, since deflating the price changes by the cumulative inflation controls for the differences in price changes that arise from differentiated lengths without change. Our results considering a nominal specification are analogous and are available in the Online Appendix.

3.2 Baseline specification

Our baseline specification augments the MRPT regression to include price age and an interaction of age and cumulative depreciation. We run the following regression conditional on price change:

$$\Delta p^R_{s,t} = \beta \Delta_c \mathrm{RER}_{s,t} + \delta_0\ age_{s,t} + \delta_1\ (age_{s,t} \times \Delta_c \mathrm{RER}_{s,t}) + \gamma' X_{s,t} + \epsilon_{s,t} \tag{2}$$

3.3 Controls

The baseline estimations control for year, month, and generic item fixed effects. Additionally for both posted and regular prices specifications we control for sale-related price changes. For posted prices we include dummy variables for sale-related price changes: changes at the beginning, during, and at the end of sales. For regular prices we also include a sale-related dummy variable for the price changes generated by sales that ends in a different regular price. This type of changes arise because in the construction of these prices it is assumed that they are equal to the last observed regular price during the sale period. Hence when sales ends in a different regular price there will be a regular price change of the difference between the new and the last observed regular price. This control is relevant since in our data only around 42% of sales return to their previous regular level.[12] For the rest of the sales that do not return

[11] Alternative specifications have also been implemented with price micro data, for example the life-long pass-through (LFPT), also from Gopinath and Itskhoki (2010), that measures the cumulative pass-through over products' entire life.

[12] This percentage is smaller compared to the evidence from the US. Klenow and Kryvtsov (2008) reports that about 60% of sales reported in the US CPI micro data return to their previous regular price.

to their previous level, 40% of the total ends in a lower regular price and 18% at a higher regular price. Reflecting this previous fact, the estimated coefficient for the end-of-sale regular price changes dummy is negative around 5%. Finally, in a similar fashion as for the NER, we also control for the pass-through of two additional cost push shocks: the price of commodities and the producer price of electricity in Mexico.

3.4 Price Age and Pass-Through: All observations

Table I presents the results for our baseline specification (2). Column (1) shows that average passthrough is equal to 0.037. This number is consistent with the previous literature, as we find that average MRPT is low. Berger and Vavra (2015) obtain a coefficient of 0.144 for the same specification using US import data.

Column (2) includes *age* as a regressor; this raises the estimate of average passthrough and yields a negative coefficient for age. Column (3) includes also the interaction between age and MRPT, and $\delta_1 = -0.006$ is the main coefficient of interest as it measures how passthrough changes with price age. To fix ideas, let $\mathcal{P}(age)$ be the response to a 1% cumulative change in the exchange rate by age, ignoring other regressors. Given our preferred estimates, we obtain:

$$\mathcal{P}(age) \equiv \widehat{\beta} + (\widehat{\delta}_0 + \widehat{\delta}_1)age = 0.083 - 0.007\,age$$

Since $|\widehat{\delta}_1| > |\widehat{\delta}_0|$ and $\widehat{\delta}_1 < 0$, we obtain a negative slope. Specifically, in our preferred specification, this measure of pass-through $\mathcal{P}$ is 50% smaller for prices that are six-months old $\mathcal{P}(6)$ compared to prices that are one-month old $\mathcal{P}(1)$.

Table I: Price Age and Exchange Rate Pass-Through

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MRPT (β)	0.037*	0.047**	0.083***	0.098***	0.081***	0.076***	0.089***
Age (δ_0)		-0.002***	-0.001***	-0.001***	-0.001***	-0.002***	-0.002***
Age × MRPT (δ_1)			-0.006***	-0.007***	-0.006***	-0.006***	-0.004***
End of Sale †				-0.052***	-0.052***	-0.051***	-0.051***
Commodities Shock							0.026*
Electricity Shock							-0.019
Time FE	No	No	No	No	Yes	Yes	Yes
Generic Item FE	No	No	No	No	No	Yes	Yes
R^2	0.0002	0.0019	0.0021	0.0132	0.0169	0.0206	0.0208
N				1,062,834			

Notes: The dependent variable is the size of product level price changes deflated by the cumulative change in the CPI ($\Delta p^R_{s,t} = \Delta p_{s,t} - \Delta_c CPI_{s,t}$). The superscripts ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, considering robust standard errors clustered at generic item level. † denotes a dummy variable. Time FE denotes controls for month and year fixed effects. The commodities and electricity shocks pass-through are introduced as the cumulative change during the price spell before the change, analogous to the ERPT.

3.5 Price Age and Pass-Through: Age Quartiles

The age quartiles are constructed considering, by separate, each generic item duration distributions. For each age quintiles at the generic level, we run the following regression:

$$\Delta p^{R}_{s,t} = \beta \Delta_c \text{RER}_{s,t} + \gamma' X_{s,t} + \epsilon_{s,t} \tag{3}$$

Table II: Exchange Rate Pass-Through by Price Age Quartiles

	$Q1$ $age_{s,t} \leq age_g^{0.25}$		$Q2$ $age_g^{0.25} < age_{s,t} \leq age_g^{0.50}$		$Q3$ $age_g^{0.50} < age_{s,t} \leq age_g^{0.75}$		$Q4$ $age_g^{0.75} < age_{s,t}$	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
MRPT	0.085***	0.091**	0.033	0.023	0.048**	0.051	0.002	0.054
End of Sale †		-0.035***		-0.041***		-0.066***		-0.093***
Commodities Shock		0.043*		0.019		0.011		-0.002
Electricity Shock		-0.034		-0.007		-0.007		-0.013
Time FE	No	Yes	No	Yes	No	Yes	No	Yes
Generic Item FE	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.00046	0.00927	0.00026	0.03651	0.00048	0.05415	0.00001	0.08314
N	657,988		146,928		105,395		52,861	

NOTES: MRPT regressions conditional on the price spell age prior the price change. The dependent variable is the size of product level price changes deflated by the cumulative change in the CPI ($\Delta p^{R}_{s,t} = \Delta p_{s,t} - \Delta_c CPI_{s,t}$). The superscripts ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, considering robust standard errors clustered at generic item level. † denotes a dummy variable. Time FE denotes controls for month and year fixed effects. The commodities and electricity shocks pass-through are introduced as the cumulative change during the price spell before the change, analogous to the ERPT.

3.6 Price Age and Pass-Through: Major Groups

We consider nine different major groups of goods and run the pass-through regression for each group.

$$\Delta p^R_{s,t} = \beta \Delta_c \text{RER}_{s,t} + \delta_0 \; age_{s,t} + \delta_1 \; (age_{s,t} \times \Delta_c \text{RER}_{s,t}) + \gamma' X_{s,t} + \epsilon_{s,t} \tag{4}$$

Table III shows that the interaction of age and pass-through yields a negative coefficient δ_1 for five of the groups, but it is significant for processed and unprocessed food which together account for 40% of the sample.

Table III: Price Age and Exchange Rate Pass-Through by Major Group

Major Group	MRPT (β)	Age (δ_0)	Age $\times$ MRPT (δ_1)	R^2 Adj.	N
Total Sample	**0.090*** **	**-0.002*** **	**-0.007*** **	**0.018**	**1,062,834**
Processed Food	0.036	-0.001***	-0.005**	0.042	204,931
Unprocessed Food	0.218***	0.000	-0.016*	0.019	613,693
Household Goods	-0.030	-0.003***	0.003	0.039	39,920
Household Durables	0.099**	-0.003***	-0.003	0.068	30,303
Apparel	-0.002	-0.002***	0.001	0.057	55,355
Transportation Goods	0.043***	-0.002***	-0.001	0.064	14,142
Recreation Goods	0.055	-0.002***	0.000	0.042	13,625
Health and P. Care Goods	-0.009	-0.004***	0.001	0.052	90,865

NOTES: Results for specification (6) of Table I distinguishing by sample major groups. The dependent variable is the size of product level price changes deflated by the cumulative change in the CPI ($\Delta p^R_{s,t} = \Delta p_{s,t} - \Delta_c CPI_{s,t}$). The superscripts ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, considering robust standard errors clustered at generic item level.

4 Price Age and Cross-Sectional Dispersion of Price Changes

4.1 Product-Level Dispersion and Price Age

Let $disp^s$ be a measure of price dispersion at the product level. The following specification is used in Berger and Vavra (2015) and we augment it with price age:

$$\Delta p^R_{s,t} = \beta \Delta_c \text{RER}_{s,t} + \theta_0 disp^s + \theta_1 \left(disp^s \times \text{RER}_{s,t}\right) + \delta_0 \ age^s_t + \delta_1 \left(age^s_t \times \text{RER}_{s,t}\right) + \gamma' X^s_t + \epsilon^s_t \quad (5)$$

First, we consider our measure of dispersion to be equal to the the standard deviation of all non-zero price changes at the product level:[13]

$$disp^s \equiv std(\Delta p^r_t | r = s)$$

Columns (1) to (4) of Table IV show the results from the previous regression. We observe that product level dispersion is indeed significant and quantitatively important.

Table IV: ERPT, Price Age and Product-Level Dispersion

	(1)	(2)	(3)	(4)	(5)	(6)
β	0.054***	0.054**	0.078**	-0.036	-0.033	-0.043
δ_1			-.007***	-.002*	-0.001	-0.002
δ_0			0.001***	0.001***	0.001***	0.001***
θ_1				1.278***		1.274***
θ_0				0.105***		0.127***
η_1					0.197**	0.007
η_0					-.008***	-.016***
Beginning of Sale †		-.195***	-.195***	-.197***	-.195***	-.197***
End of Sale †		0.145***	0.147***	0.145***	0.147***	0.145***
During Sale †		-.047***	-.045***	-.048***	-.044***	-.047***
FE Generic Item	No	Yes	Yes	Yes	Yes	Yes
FE Time	No	Yes	Yes	Yes	Yes	Yes
R^2 Adj.	0.0002	0.2282	0.2289	0.2297	0.2291	0.2299
N			1,274,069			

[13]XX FK: We are eliminating one price change because of censoring. Compute first dispersion of price changes including all data, then do the left censoring.

4.2 Product-Level Dispersion and ERPT by Quartiles of $disp^s$

Now we estimate ERPT for separate quartiles of the distribution of product level dispersion. Let Q_s^q be an indicator function that takes the value of 1 if product s exhibits price change dispersion in the $q-th$ quartile of the dispersion distribution:

$$Q_s^q \equiv \mathbb{1}\{s \in q-th \text{ quartile of } disp^s\}$$

Then we estimate:

$$\Delta p_{s,t}^R = \beta \Delta_c \text{RER}_{s,t} + \sum_{q=2}^{4} \beta^q \left(Q_s^q \times \Delta_c \text{RER}_{s,t}\right) + \gamma' X_t^s + \epsilon_t^s \tag{6}$$

The following results show that it is the products with highly dispersed price changes that are generating the dispersion effects.

Table V: Dispersion Quartiles Interactions

	(1)	(2)	(3)
β	0.054***	0.054**	0.022
β^2			0.009
β^3			-0.004
β^4			0.170***
Beginning of Sale †		-.195***	-.196***
End of Sale †		0.145***	0.145***
During Sale †		-.047***	-.047***
FE Generic Item	No	Yes	Yes
FE Time	No	Yes	Yes
R^2 Adj.	0.0002	0.2282	0.2285
N		1,274,069	

4.3 Product-Level Dispersion and Frequency of Adjustment

What is the relationship between dispersion and frequency of adjustment at the product level? Menu cost pricing models predict a positive relationships between the volatility of the underlying driving process and price change dispersion, and also with the frequency of adjustment.

XXX Include some scatter plot of table with statistics of dispersion, age, frequency.

We explore this relationship with the introduction of individual frequency:

$$\Delta p^R_{s,t} = \beta \Delta_c \mathrm{RER}_{s,t} + \theta_0 disp^s + \theta_1 \left(disp^s \times \mathrm{RER}_{s,t}\right) + \delta_0\, age^s_t + \delta_1 \left(age^s_t \times \mathrm{RER}_{s,t}\right) + \phi_0 fr^s + \phi_1 \left(fr^s \times \Delta_c e^s_t\right) + \gamma' X^s_t + \epsilon^s_t \tag{7}$$

Table VI: Dispersion and Frequency Interactions

	(1)	(2)	(3)	(4)	(5)
β^{avg}	0.054***	0.054**	-0.036	-0.026	-0.041
β^{vol}			1.255***		1.284***
δ^{vol}			0.086***		0.126***
β^{fr}				0.182**	-0.003
δ^{fr}				-.016***	-.024***
Beginning of Sale †		-.195***	-.198***	-.195***	-.197***
End of Sale †		0.145***	0.143***	0.146***	0.143***
During Sale †		-.047***	-.049***	-.045***	-.048***
FE Generic Item	No	Yes	Yes	Yes	Yes
FE Time	No	Yes	Yes	Yes	Yes
$R\hat{2}$ Adj.	0.0002	0.2282	0.228895	0.2285991	0.2295829
N			1,274,069		

5 Exogenous Age Shock and Pass-Through

In January of 2014, the Mexican Government implemented a tax reform that led to an increase of different taxes: (1) the preference rate of the value added tax (VAT) in the frontier zones was eliminated to match the level of the rest of country (an increase of 11 to 16%); (2) an additional tax to refreshments and sugar drinks was implemented; and (3) the inclusion to the VAT of some goods and services which were previously exempted. Other taxes also increased with the 2014 reform, such as an increase in the income tax to high income workers and an additional increase in the price of gasolines.

We take advantage of this exogenous change in price age distribution to analyse its relation to ERPT. First we document that the behaviour of the economy six months before and six months after the VAT shock was similar. Then we conduct ERPT estimations using the price changes before and after the tax and find a significant increase in passthrough after the VAT shock.

5.1 Prices and Exchange Rates Around 2014 Tax Shock

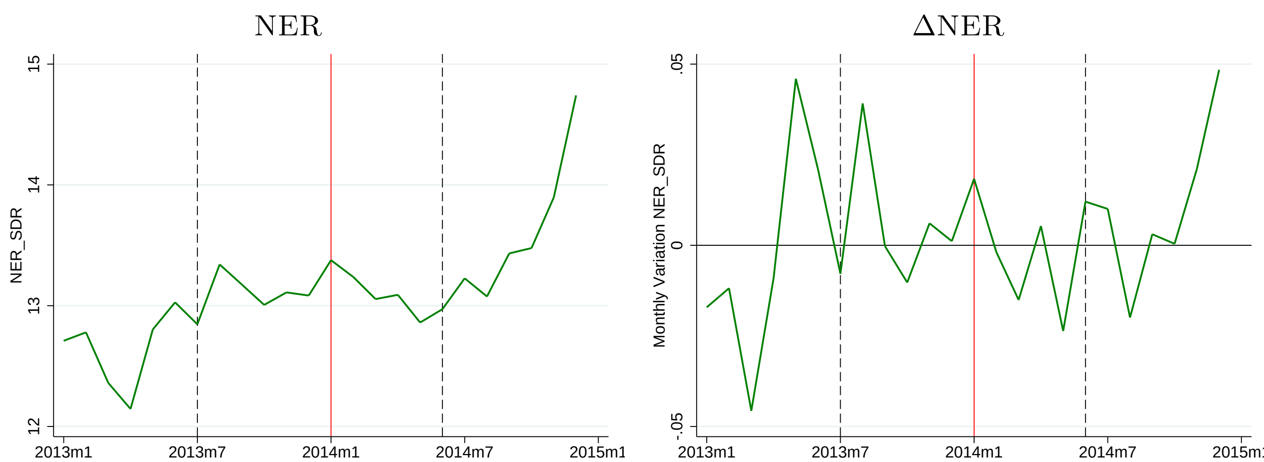
Table VII summarises age, price change, and exchange rate statistics for both samples.

Table VII: Descriptive Statistics Around VAT shock

	Before (6months)	After (6months)	Impact (Jan 2014)
Mean Age	8.1	7.3	7.2
Duration	3.2	3.5	4.8
Mean $\Delta_c NER$	1.4%	0.1%	0.5%
Mean $\Delta_c RER$	0.9%	-0.5%	-1.5%
Mean Δp	1.1%	0.9%	4.75%
Mean Δp^R	0.3%	0.0%	2.63%

Figure IV shows that the nominal exchange rate is basically flat during the pre- and post- experiment window. It is until the second half of 2014 that it experiences a large depreciation.

Figure IV: Nominal Exchange Rate Time Series



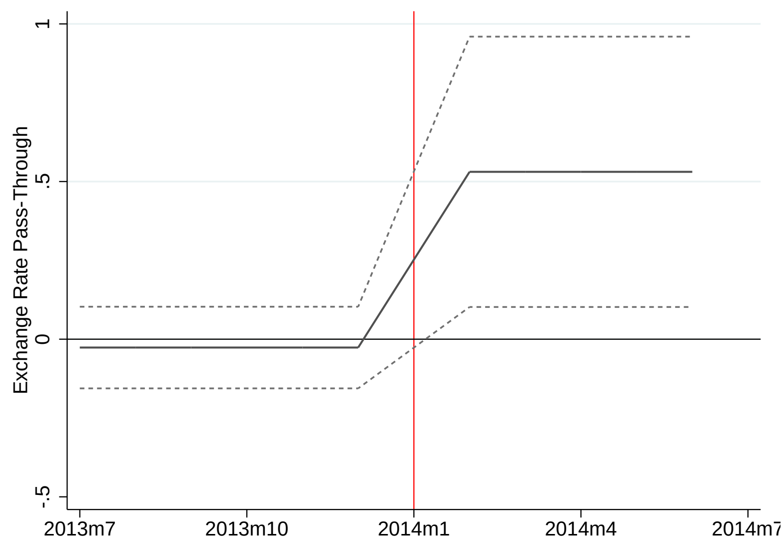
5.2 Results

In order to test our hypothesis that younger prices exhibit higher pass-through, we run our baseline specification for two sample periods consisting of six months previous to the VAT shock (July 2013 to Dec 2013 included) where the distribution of price changes was concentrated towards older prices and six months after the VAT shock (February 2014 to June 2014 included) where the distribution of price changes was concentrated towards younger prices.

$$\Delta p^R_{s,t} = \beta \Delta_c \text{RER}_{s,t} + \gamma' X^s_t + \epsilon^s_t \tag{8}$$

Our estimates indicate that average pass-through before the tax shock is $\hat{\beta}_{pre2014} = -0.05$ and after the tax shock is $\hat{\beta}_{post2014} = 0.55$.

Average Pass-Through Before And After 2014 Tax Shock



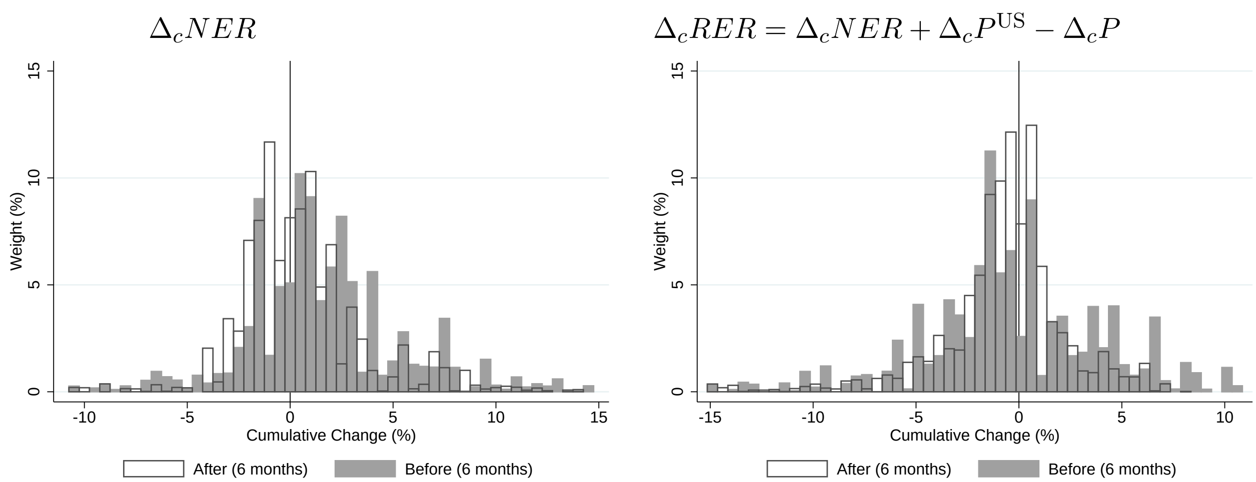
5.3 Asymmetric pass-through

A first potential explanation for our results is that there is a different response of prices to exchange rate appreciations than depreciations. We also analyze the distributional characteristics of the cumulative real and nominal exchange rate for all the price spells that end during the 6 months after and before the VAT change. The figures show that the ERPT explanatory variable is similar before and after the shock.

5.4 Seasonality

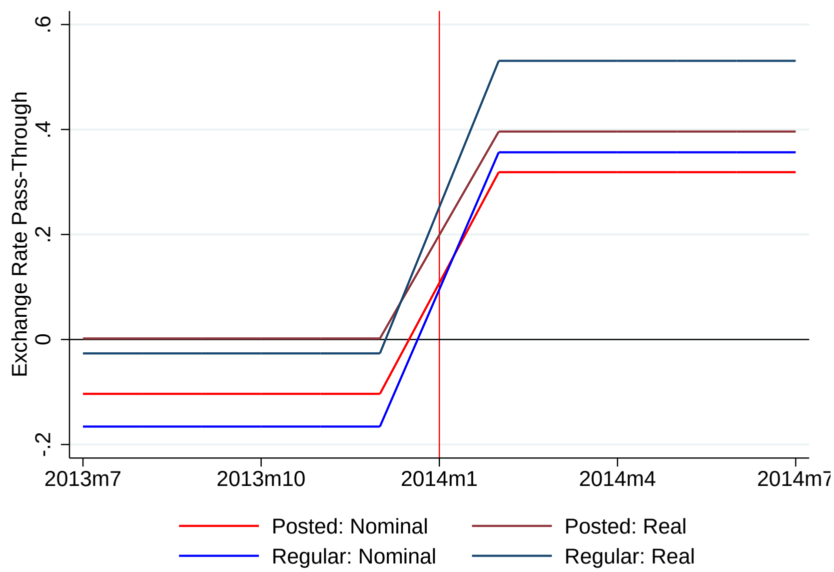
A second potential explanation could be seasonality, in which the first months of the year present higher pass-through than later months (due, for example, to calendars of contract revisions) or that exchange rate depreciation is more pronounced in some months than others.

Figure V: Cumulative Exchange Rate (Nominal and Real)



5.5 Robustness

Jan 2014 - All Specifications Larger Window



6 Conclusions

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A Robustness

A.1 Average age

Let age^s be the average age for each product s across all time periods. Note that age^s acts as a specific product fixed effect. Berger and Vavra (2015) run a similar regression using the average frequency of adjustment $freq^s$ as a measures of price age and do not find significative effects either. Therefore, our effects refer to a product characteristic that changes over time that cannot be captured by a fixed effect.

$$\Delta p_t^s = \beta \Delta e_t^s + \gamma' X_t^s + \delta_0 \ age^s + \delta_1 \ (age^s \times \Delta e_t^s) + \epsilon_t^s \tag{9}$$

A.2 Higher order terms in age

We also add higher order terms in age. The following is a quadratic specification.

$$\Delta p_t^s = \beta \Delta e_t^s + \gamma' X_t^s + \delta_0 \ age_t^s + \delta_1 \ (age_t^s \times \Delta e_t^s) + \delta_2 \ (age_t^s)^2 + \delta_3 \ ((age_t^s)^2 \times \Delta e_t^s) + \epsilon_t^s \tag{10}$$

A.3 Tradable and non-tradables

We separate products in tradable and non-tradables and run the regression adding a dummy $trade = 1$ if the good is tradable and $trade = 0$ otherwise.

$$\Delta p_t^s = \beta \Delta e_t^s + \gamma' X_t^s + \delta_0 \ age_t^s + \delta_1 \ (age_t^s \times \Delta e_t^s) + \chi \ trade + \epsilon_t^s \tag{11}$$