Domestic Price Dollarization in Emerging Economies*

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Abstract

This paper studies the dollarization of prices in retail markets of emerging economies. We develop a model of the firm's optimal currency choice in retail markets in inflationary economies. We derive theoretical predictions regarding the optimality of dollar pricing, and test them using data from the largest e-trade platform in Latin America. Across countries, price dollarization is positively correlated with asset dollarization and inflation, and negatively correlated with exchange rate volatility. At the micro level, larger sellers are more likely to price in dollars, and more tradeable goods are more likely to be posted in dollars. We then show that the currency of prices determines the short-run reaction of both prices and quantities to a nominal exchange rate shock.

Keywords: currency choice, prices, dollar, exchange rate, pass-through.

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1 Introduction

The currency in which prices are denominated is relevant for the macroeconomy. First, since prices are rigid in the short-run, the currency of prices affects the transmission of nominal exchange rate shocks to domestic prices and economic activity. Second, a large share of prices set in foreign currency undermines the value of the local currency as a unit of account and poses challenges to the conduct of monetary policy. Based on the predominance of the use of the local currency in the domestic markets of advanced economies, most of the literature on this topic focuses on the currency of invoicing in international trade. However, anecdotal evidence suggests that currency choice can be an active margin when setting domestic prices in emerging economies. In this paper, we conduct an empirical study, guided by theory, to document the importance of dollar pricing in domestic markets of emerging economies and assess its macroeconomic implications.

We develop a tractable model of the optimal currency choice of prices for a firm operating in a domestic retail market. We then test the model's predictions by conducting an empirical study of currency choice in the domestic markets of various Latin American economies. We first show that a significant fraction of prices in domestic markets is set in US dollars, and that there is large heterogeneity in the use of dollar pricing across countries. Consistent with the model's predictions, we show that countries with more dollar pricing have higher levels of households' asset dollarization, lower exchange rate volatility, and, to a lesser extent, higher inflation. Within each country, larger sellers are more likely to price in dollars, and more tradeable goods are more likely to be posted in dollars. Finally, we show that the currency of prices determines the short-run reaction of prices and quantities to a nominal exchange rate shock. This implies that the currency choice of prices has implications for the allocative effects of exchange rate movements.

The paper starts off with a model of the currency and price choices of firms in retail markets. The framework builds on the model of Gopinath et al. (2010), and incorporates two key departures. First, it considers the problem of a firm operating in the retail market. Second, it extends the analysis to economies with inflation. In the model, the firm chooses the currency so that the evolution of its sticky preset price tracks the optimal flexible price in the closest possible way. Therefore, the firm prices in foreign currency when the desired medium-run pass-through is above a cutoff level that depends on the properties of the inflation rate and the nominal exchange rate. We show that dollar pricing is more attractive when inflation is higher—since dollar pricing avoids the erosion of the real value of local currency prices caused by inflation—and less attractive when the exchange rate is more volatile. We also show that the currency choice is affected by the demand for the good and, in particular, dollar pricing is more likely when there is a larger share of the consumer's wealth that is denominated in dollars. Finally, we show that dollar pricing is optimal for goods whose costs, measured in local currency, co-move more strongly with the exchange rate. Therefore, goods that are more tradable and whose input prices have a higher exchange rate pass-through, as well as goods sold by firms that have more dollar-denominated debt, are more likely to be priced in dollars.

We then conduct an empirical study of the currency choice in the domestic markets of various Latin American economies by analyzing novel high-frequency data from the largest e-trade platform in Latin America. We also document that our findings are relevant for broader aggregates that go beyond online markets. These data contain various features that make it appropriate for our analysis. First, unlike official CPI data, it contains the currency of denomination of prices. Second, the data allow for a comparable analysis across countries and markets. Third, unlike most previously studied datasets, these data contain information on prices and quantities sold.

We begin the empirical work by documenting aggregate levels of price dollarization across countries. The data show that, on average, the share of prices in dollars is 30% for goods, 34% for vehicles, and 54% for real estate units. These figures mask significant heterogeneity across countries. Consistent with the model's predictions, price dollarization is positively correlated with asset dollarization (as measured by the share of bank deposits in dollars). Additionally, we find a negative cross-country correlation of price dollarization and nominal exchange rate volatility, and a positive, albeit mild, correlation of price dollarization with past inflation. We also find a positive correlation between price dollarization and the pass-through of exchange rate to import prices, and trade openness.

We then examine the empirical determinants of the currency choice of prices within countries. First, we assess whether the degree of tradeability of goods is relevant in determining the currency choice of prices. For this, we assign a tradeability index to each listing of goods by combining official sectoral trade and output data from Argentina and Uruguay. Consistent with the theory, we find that goods that are more tradeable are indeed more likely to be priced in dollars. Second, the model also predicts a relationship between the currency of prices and the firms' currency of debt. Data limitations impede us to test this relationship directly. Given the previously documented positive relationship between firms' size and the share of debt in dollars, we indirectly test the model's prediction by analyzing the relationship between price dollarization and firms' size. We find that larger sellers—measured by their revenues—are more likely to set prices in dollars. In particular, small sellers price goods almost exclusively in local currency, regardless of the country.

Next, we study the relationship between currency choice of prices and exchange rate pass-through. First, we find that the currency of prices determines the entirety of the pass-through in the short run, confirming the findings of previous literature. Second, we estimate currency-specific pass-through conditional on a price change, which constitutes an empirical measure of medium-run pass-through. According to the theory, dollar (local currency) prices should have a medium-run pass-through that is higher (lower) than a cutoff that depends on inflation and exchange rate volatility. We test this prediction and find that the model correctly predicts currency choice in most markets and more disaggregated categories of goods.

We further explore whether nominal exchange rate shocks differentially affect quantities sold through their effect on prices. More specifically, we estimate similar short-run pass-through regressions to estimate the dynamic effects of nominal exchange rate shocks on quantities sold of goods posted in dollars relative to similar goods that are posted in local currency. For example, for the case of Uruguay, we find that a depreciation of the nominal exchange rate of 10% has an associated decrease in the quantities sold of goods posted in dollars relative to goods posted in local currency of 18% three months after the devaluation. Given the stickiness of prices in the short run, this estimate translates into a short-run elasticity of demand of 1.8. An implication of our findings is that the currency choice of prices is relevant for understanding the transmission of nominal exchange rate shocks to allocations in the economy. These findings contribute to the empirical literature on pass-through that has successfully shown that the currency choice of prices is relevant for understanding the pass-through of nominal exchange rate to prices and quantities at the border, but is more silent regarding its allocative effects in domestic markets.

Finally, we demonstrate that our findings are relevant for broader aggregates of the economy and go beyond the workings of the online marketplace. To do so, we investigate whether the share of prices in dollars that we measure in the data from the online platform correlates with the degree of pass-through estimated on the official CPI data. We study this relationship across countries and also within one country across narrow types of goods. First, we document that countries with larger levels of dollarization—as measured by aggregate data from the online platform—have higher degrees of pass-through to aggregate official CPI data at all horizons. Second, we perform a similar analysis with disaggregated CPI data from Uruguay. We compute good-specific degrees of pass-through, and good-specific shares of prices posted in dollars using data from the online platform. We then show that there is a steep relationship between the degree of pass-through and the share of price dollarization at the good level, with more dollarized goods having larger pass-through on impact and over longer horizons.

Related Literature. Our paper is related to the growing literature that studies the macroeconomic effects of the currency of denomination of prices in international markets, and the relationship between prices and exchange rates. Burstein and Gopinath (2014) provide a survey of recent advances in this topic. A large theoretical and empirical literature has focused on the determinants of firms' currency choice of international prices, and the implications for the pass-through of exchange rate shocks to prices of internationally traded goods (see, for example, Engel, 2006; Goldberg and Tille, 2008; Gopinath et al., 2010; Goldberg and Tille, 2016; Mukhin, 2018; Corsetti et al., 2018). Recent contemporaneous work has also shown that the currency choice in border prices determines the allocative effects of exchange rate shocks (see, Cravino, 2018; Amiti et al., 2019; Corsetti et al., 2019; Auer et al., 2021). Another set of papers have analyzed the pass-through of exchange rate shocks to domestic prices, integrating the analysis of border and retail pricing theoretically (see, for example, Burstein et al., 2003, 2005; Corsetti and Dedola, 2005; Burstein et al., 2007; Corsetti et al., 2009), and empirically (see, for example, Auer et al., 2021). We contribute to this literature along two dimensions. First, we document for the first time that currency choice is an active margin when setting prices in domestic markets in emerging economies, and that there is selection into dollar pricing as predicted by our theory. Second, we show that this margin is relevant for the transmission of exchange rate shocks to both prices and allocations in retail markets.

Our paper is also related to the literature that studies financial dollarization and the global role of the dollar. One set of papers study the implications of the use of an external currency as a means of payment and a unit of account (see, for example, Alesina and Barro, 2002; Uribe, 1997; Arellano and Heathcote, 2010; Ize and Levy Yeyati, 2003; Rappoport, 2009; Drenik et al., 2018, 2021). Another recent set of papers study the predominance of the dollar in denominating international securities and international prices (see, for example, Farhi and Maggiori, 2017; Gopinath and Stein, 2018; Maggiori et al., 2020; Gopinath et al., 2020; Egorov and Mukhin, 2020). We contribute to this literature by documenting that the dollar is also used as a unit of account of domestic prices in emerging economies.

The paper proceeds as follows. Section 2 presents the model and derives its testable implications. Section 3 describes the data used in the main analysis. Section 4 conducts an analysis of the currency denomination of prices across and within countries, and tests the theoretical predictions of the model. Section 5 relates currency choice with exchange rate pass-through to prices and quantities. Section 6 argues that currency choice is relevant for the macroeconomy, and Section 7 concludes.

2 A Model of Domestic Price Dollarization

In this section, we develop a theoretical model of a firm's currency and price choices. The model builds on the work of Gopinath et al. (2020), and generalizes it to study the problem of firms that operate in retail markets in inflationary economies. The objective of the theoretical analysis is to serve as a guide for the empirical analysis and to derive a set of predictions that we later test in the data. Here, we focus on the model description and main predictions. Appendix A provides further details and results.

We study the partial-equilibrium problem of a single domestic retailer that is choosing the currency of denomination and price of its goods to maximize profits in a monopolistically-competitive market. We first describe the demand structure that the firm faces and then analyze the firm's problem.

Demand for goods– Consider a continuum of households that have preferences over a constant-elasticity-of-substitution consumption aggregator over different varieties. A household's demand for each good variety i at time t is given by

$$C_{it} = \frac{W_t}{P_t^{\text{cpi}}} \left(\frac{P_{it}}{P_t^{\text{cpi}}} \right)^{-\sigma}, \tag{1}$$

where P_{it} is the price of good i, $P_t^{\text{cpi}} = \left(\int P_{it}^{1-\sigma} \text{d}i \right)^{\frac{1}{1-\sigma}}$ is the ideal price index, and W_t is the household's wealth or income, all expressed in local currency.

Firm's technology– Firm i produces good variety i and has access to the following production technology that uses tradable and non-tradable inputs, Y_{it}^T and Y_{it}^N, respectively, to produce output Y_{it}:

$$Y_{it} = \left(\left(Y_{it}^T\right)^\eta \left(Y_{it}^N\right)^{1-\eta} \right)^\gamma,$$

where $0 < \eta < 1$ is the share of tradable input used in production, and $0 < \gamma \leq 1$ governs the degree of decreasing returns to scale. We introduce decreasing returns to scale as a simple way to make optimal prices respond to demand shifters. We interpret the tradable and non-tradable inputs used in production in a broad way. For example, for the case of imported goods, which constitute a significant fraction of the goods analyzed in the dataset, the tradable input would correspond to the good purchased at the border, and the non-tradable input would correspond to local services associated with the retail activity (e.g., distribution, advertising and storage services). As we specify below, the main difference between these two inputs is how their prices, P_t^T and P_t^N, respectively, co-move with the exchange rate.

We assume that firms have to pay a fraction ν of their factors of production before production takes place, and can finance these production costs at an interest rate i_t.[1] We introduce working capital to connect a firm's pricing decisions with its financial decisions. Cost minimization yields the following cost function for producing Y_{it} goods

$$\mathcal{C}(Y_{it}) = \left(\frac{P_t^T}{\eta}\right)^\eta \left(\frac{P_t^N}{1-\eta}\right)^{1-\eta} Y_{it}^{1/\gamma} \left(1 + \nu i_t\right). \tag{2}$$

Costs are increasing in the prices of both intermediate inputs, the quantity produced due to decreasing returns to scale, and borrowing costs. The flow profits of a firm are given by

$$\Pi_t = P_{it} C_{it} - \mathcal{C}(C_{it}),$$

where we used the equilibrium condition $Y_{it} = C_{it}$. Firms are monopolistically competitive and take into account the effect of their price choices on demand.

[1] The timing assumption is that firms purchase their factors after observing shocks, and a fraction ν of them needs to be paid before production takes place. This requires firms to finance that share of factor payments with intra-period loans that entail an interest rate of i_t. This timing assumption is commonly used in models that assume the presence of working capital (e.g., Neumeyer and Perri, 2005; Jermann and Quadrini, 2012).

Nominal rigidities– We consider the problem of a firm that faces nominal rigidities à la Calvo (1983) and can choose to denominate its prices in local currency or foreign currency (the US dollar, in our setting). The firm can adjust its price and the currency of denomination of its price each period with an exogenous probability $(1-\theta)$. Henceforth, we use small letters to denote the log of a variable.

Exogenous processes– We assume that the log of the exchange rate, defined as local currency per unit of foreign currency, follows a random walk with drift

$$e_{t+1} = e_t + \mu + \epsilon_{et+1}, \tag{3}$$

where ϵ_{et} is white noise. We assume that $\mu \geq 0$, which is the empirically relevant case for the set of emerging economies we analyze, since all of them exhibit higher rates of inflation than the US and a positive drift in the nominal exchange rate vis-a-vis the US dollar.

We assume that the log of the ideal price index, and the prices of tradable and non-tradable inputs, follow

$$p_t^j = \alpha_j e_t + (1-\alpha_j)\,\mu t + \epsilon_t^j,$$

where $0 \leq \alpha_j \leq 1$ is the pass-through of exchange rate fluctuations to price j, and ϵ_t^j is white noise, for $j = \{\text{cpi}, T, N\}$. According to this assumption, all prices grow at the rate μ, implying that μ is both the expected depreciation and inflation rate. We further assume that $\alpha_T > \alpha_N$, or equivalently, that the exchange rate pass-through to the price of tradable inputs is larger than the pass-through to the price of non-tradable inputs. This assumption is motivated by the fact that most of the imports of these countries are denominated in US dollars (Gopinath, 2016), whereas on the other hand, non-tradable services are often quoted in local currency (see Burstein et al., 2005, for supporting evidence of this assumption).

We consider the case in which firms can finance working capital with a combination of local and foreign currency debt. This implies that the firm's interest rate is given by

$$i_t = \omega\left(i_t^F + \Delta e_t\right) + (1-\omega) i_t^L,$$

where Δe_t is the depreciation rate; i_t^L and i_t^F are the nominal interest rates in local and foreign currency, respectively, which, for simplicity, we assume to be white noise; and ω is the share of debt denominated in foreign currency.

Finally, we assume that a fraction of the households' wealth/income is denominated in foreign currency. In particular, we assume that the log of households' wealth, expressed in local currency, is given by

$$w_t = \alpha_w e_t + (1 - \alpha_w)\,\mu t + \epsilon_t^w,$$

where $0 \leq \alpha_w \leq 1$ is the share of wealth denominated in foreign currency, and ϵ_t^w is white noise.[2]

Optimal currency choice– In Appendix A, we show that the main insights in Gopinath et al. (2020) carry over to our setting. The following proposition summarizes the main results.

Proposition 1. *Up to a second order approximation, a firm chooses to set prices in local currency if and only if*

$$\frac{1}{2}\left(1 - \left(\frac{1}{1-\rho\theta}\right)\frac{\mu^2}{\text{Var}\left(\epsilon_e\right)}\right) > (1-\rho\theta)^2 \sum_{s=1}^{\infty} (\rho\theta)^{s-1} s \frac{\text{Cov}_t\left(e_{t+s}, \tilde{p}_{t+s}\right)}{\text{Var}_t\left(e_{t+s}\right)} \equiv MRPT. \tag{4}$$

In addition, let $\mathcal{L}$ denote the firm's value of setting prices in local currency relative to setting them in foreign currency. Then, all other things equal, firms are more likely to choose to price in foreign currency when:

1. *the inflation rate is higher: $\frac{\partial \mathcal{L}}{\partial \mu} \leq 0$ when $\mu > 0$,*
2. *the variance of exchange rate shocks is lower,*
3. *the dollarization of households' assets is higher: $\frac{\partial \mathcal{L}}{\partial \alpha_w} \leq 0$,*
4. *the exchange rate pass-through of the tradable inputs is larger: $\frac{\partial \mathcal{L}}{\partial \alpha_T} \leq 0$,*
5. *the share of tradable inputs is larger: $\frac{\partial \mathcal{L}}{\partial \eta} \leq 0$,*
6. *the dollarization of firms' debt is higher: $\frac{\partial \mathcal{L}}{\partial \omega} \leq 0$.*

Proof. See Appendix A. □

[2] Our model focuses on short-run dynamics of prices and currency choices, and takes asset dollarization as exogenous. This assumption is motivated by the fact that in the data asset dollarization is a slow moving variable with a high degree of path dependence, an observation that the literature refers to as hysteresis (see, e.g., Ize and Levy Yeyati, 2003). For a model that endogenizes currency choices in credit contracts see Drenik et al. (2021).

The first part of Proposition 1 shows that currency choice is determined by medium-run exchange rate pass-through (MRPT), a sufficient statistic that captures the co-movement between the exchange rates and the optimal flexible price $\tilde{p}_t$. Since setting prices in the foreign currency is a form of indexation, firms optimally choose this currency when desired MRPT is above a given threshold. Relative to Gopinath et al. (2020), a non-zero inflation makes the threshold decreasing in inflation. This implies that higher inflation rates makes foreign currency pricing more attractive. The reason is that foreign currency pricing is a way of indexing prices to inflation. The higher the inflation rate, the larger the erosion of local currency prices relative to foreign currency prices, and the larger the incentives to choose the foreign currency.

To understand how each model feature affects MRPT, we perform a comparative statics analysis in the second part of Proposition 1. The first result follows from the discussion above on the role of inflation on currency choice. According to the second result, dollar pricing is more likely when the variance of exchange rate shocks is lower. Firms base their currency choice on the indexation features of each currency and the desired MRPT. Since the latter driver affects currency choice as long as exchange rates are volatile, the former driver dominates when the variance of exchange rate shocks becomes low enough and firms choose to price in foreign currency. For example, consider the limiting case in which the variance of the exchange rate is zero. In this case, all firms prefer the foreign currency because of its indexation benefits that maintain the real value of prices. As the variance of the exchange rate increases, two possibilities arise. First, if desired MRPT is high, the higher variance of the exchange rate reinforces the preference for foreign currency. Second, if desired MRPT is low, the higher variance of the exchange rate makes firms value more the local currency, in which case firms' optimal choice eventually changes from foreign to local currency if the variance becomes large enough.

The remaining predictions regard how structural parameters affect currency choice through their effects on desired MRPT. The third result states that dollar pricing is more likely when there is larger dollarization of households' wealth. When there is larger households' asset dollarization, exchange rate fluctuations precipitate wealth revaluations that shift the demand for consumer goods. Due to the presence of decreasing returns to scale, firms would like to adjust prices in response to movements in demand, and setting prices in dollars is a way of doing so. The fourth result states that goods whose tradable input prices have a higher exchange rate pass-through are more likely to be priced in dollars. This is because the cost of those goods co-varies more strongly with the exchange rate and dollar pricing is a way of making the price adjust to these fluctuations in costs. A related implication is the fifth result, which states that more tradable goods are more likely to be priced in dollars. This is due to the assumption that the exchange pass-through is larger for tradable inputs than it is for non-tradable inputs. In various cases, the tradable input corresponds to the good purchased at the border, whose price is commonly set in dollars and therefore co-moves strongly with the exchange rate. Finally, firms with more dollarized debt are more likely to set dollar prices, since exchange rate fluctuations affect more the financial component of their costs, and firms would like to adjust their prices in response to costs movements.

In the next sections, we test all the predictions of the theory using both cross-country micro- and macro-level data.

3 Data Description and Representativeness

3.1 Data Description

The main dataset used in our analysis of the currency of denomination of prices comes from the leading e-trade platform in Latin America: Mercado Libre (*www.mercadolibre.com*). The company was founded in 1999, currently operates in multiple countries, and has more than 190 million users. In 2017, the platform sold a combined gross merchandise value of USD 11.8 billion (26% of all e-commerce sales in Latin America)—see *Retail e-commerce sales in Latin America*.

Buyers and sellers transact on the platform as follows. Sellers create a listing that includes a title describing the good, a picture and more detailed description of the good, including the selling price. Buyers can find goods by either searching by name or navigating a category tree that categorizes goods in different groups. Once a buyer locates a good of interest, she can click on the listing and obtain more information about the good. Figures B.1 and B.2 in the Appendix show the outcome of a search for a "Playstation 4" in Mercado Libre-Uruguay. Finally, the buyer decides whether to make the purchase. A more detailed description of the relevance of Mercado Libre in the online market in Latin America, how the platform operates, and how payments are made can be found in Appendix C.1.

The data collection process is facilitated by the provision of APIs by the platform, which is a set of codes that can be used to download data directly from their servers. A description of the data collection process is provided in Appendix C.2. At the listing level, we store daily information on the start and end dates of the listing, seller identifiers, the title of the listing describing the good, the unit price before taxes, the currency of denomination of prices, and the quantities sold. Before using the data, we clean it in various dimensions to render it suitable for analysis. We provide details of the cleaning procedure in Appendix C.3.

The platform asks sellers to categorize the good being sold according to a pre-specified set of choices. Each good is placed within a category tree that has multiple levels. The first level contains goods defined broadly, such as computers, and health/beauty. At the other extreme, the narrowest categories contain very detailed goods, such as an iPhone X 32GB. Since the classification system on the platform is not standard, we compare it to other product classifications, such as the 2018 US Harmonized System (HS). In Table B.1, we show that for a subsample of relevant products, the platform's classification at level 3 is comparable to, or even more specific than, the HS classification used in international trade at 6 or 8 digits. Thus, the category tree at level 3—which is the level at which we group goods in most of the analysis—contains goods that are narrowly defined.

The two most novel pieces of information are the currency of denomination of prices and quantities sold. In most countries, sellers can choose between two currencies: the local currency and the US dollar. With the rare exception of anecdotal evidence, to the best of our knowledge this is the first paper to include data on currency choice for goods sold domestically. In addition, we have high-frequency data on quantities sold, which is not common in datasets from online markets. Having this information allows us to demonstrate that currency choice not only matters for prices, but also for quantities.

There are several benefits of using data from this platform. First, it contains data from multiple countries and types of goods organized in a consistent way. The platform operates in all major countries in Latin America. Our sample of countries varies depending on the type of analysis we pursue. For the cross-country analysis we use data from 15 countries, namely Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, the Dominican Republic, Guatemala, Honduras, Mexico, Nicaragua, Panama, Paraguay, Peru, and Uruguay. For the within-country analysis of price dollarization we study a subset of these countries. In Appendix C.4 we justify the choice of sample of countries for each exercise. The second benefit of the data is the coverage; the range of goods offered for sale and transacted on this platform is wide. In addition to being a marketplace for consumer goods, the platform expanded into the real estate and vehicles market by allowing users to list online ads and seller's contact information. Thus, the results we present come from three broad markets and show that the facts are not specific to a narrow group of goods. In Appendix D, we discuss the representativeness of the data relative to the average consumption basket in Uruguay, our flagship example of price dollarization in domestic markets.

The third benefit of the data is the high-frequency nature of the data collection process. Although our time span only covers March-October 2018, our data are collected on a *daily* basis. This allows us to provide cleaner evidence on the effects of currency choices on the response to high-frequency shocks like those that affect the exchange rate. Additionally, the relatively short time span is not a major concern, since the sample period contains episodes of medium and large devaluations, which we exploit in our empirical analysis.

In addition to these data, our analysis makes use of historical data from the platform covering the 2003-2012 period. This dataset includes a similar set of variables, but are only recorded when the listing is created or a transaction is made, and is available only for Argentina and Uruguay. We use the historical data to analyze the relationship of tradeability of goods and the currency of their prices in Section 4.2. We complement the analysis with data on aggregate and disaggregated price indices, and sectoral trade and value added across all major Latin American countries. We describe these data in Appendices C.5 and C.6.

3.2 Summary Statistics

Tables B.2-B.4 and Figure B.3 in the Appendix present descriptive statistics of the data. Here, we provide a summary of the most relevant ones. Overall, we have data for 43.7 million listings and 3.5 million sellers. Among those countries that display some degree of price dollarization, the biggest markets are Argentina, Mexico, Peru, and Uruguay.[3] First, we provide summary statistics for sellers. On average, sellers have 4.8 years of experience using the platform and, in terms of the historical number of transactions, they made on average 137 sales when conditioning on making at least one. During our window of observation, sellers had on average 7 active listings and made 7.5 sales (34 when conditioning on making at least one sale). Median revenue conditional on having positive sales is USD4,600. In addition,

[3]Given the size of the dataset, we took a random sample in which the sampling unit is the seller (the size of the random sample in each country is shown in Table B.2). After taking the random sample, we end up with 434 million listing-day observations across all markets and countries.

most sellers/listings are quite active in the platform: More than 75% of all listings in the goods market belong to sellers that had at least 25 sales during the window of observation (less than 10% of listings belong to sellers without sales).[4]

Next, we provide descriptive statistics for the types of goods sold on the platform. In the goods market, average unit prices range from USD44 in Clothing to USD330 in Cameras and accessories. In addition, there are the real estate and vehicles markets, in which the average listed prices are USD161,400 and USD10,200, respectively. In general, the set of goods sold on the platform is tilted toward durables; examples of most common groups of goods at level 3 are: portable speakers, SD memories, Playstation 4, electric guitars, sneakers for men, hard drives. Additional summary statistics are provided in Appendix C.1.

4 Stylized Facts about Price Dollarization

In this section, we document the relevance of dollar pricing in the domestic markets of various Latin American economies and perform an analysis, guided by our theory, of the variation across and within countries.

4.1 Price Dollarization across Countries

We first document that in a large number of countries, a significant share of prices is set in dollars. For this, we compute average levels of price dollarization using data from the online platform for the sample period March to October 2018. Table 1 shows the share of prices set in dollars by country, broken down by type of market: vehicles, real estate, and consumer goods. The average share of prices in dollars is 30% for goods, 34% for vehicles, and 54% for real estate. There is heterogeneity in the degree of price dollarization across countries, with significant levels of dollarization in Bolivia, Nicaragua, Paraguay, Peru, and Uruguay, and considerably lower levels in Mexico.[5]

Price Dollarization and Macroeconomic Variables– We analyze the variation in the degree of price dollarization across countries to test the predictions of the theory. We present

[4]The platform also gives special attention to a subset of sellers: official stores. These include well-known brands/firms (e.g., Adidas, Dell, Levi's, and Samsung) and large locally-known retailers in each country (e.g., the list of official stores in Uruguay can be accessed *here*).

[5]Peru exhibits significant levels of price dollarization in spite of regulation requiring prices to be quoted in local currency and, optionally, in any other currency (see Castellares and Toma, 2020). In Brazil, Chile and Colombia, price dollarization is zero due to regulation. For example, in Brazil and Colombia the use of foreign currency is limited by the fact that residents cannot open foreign-currency denominated bank accounts.

Table 1: Price Dollarization by Country

Country	Goods	Vehicles	Real Estate
Argentina	0%	9%	76%
Bolivia	42%	67%	83%
Costa Rica	2%	4%	35%
Dominican Republic	3%	15%	51%
Guatemala	7%	2%	55%
Honduras	60%	6%	30%
Mexico	0%	2%	7%
Nicaragua	84%	81%	92%
Panama	58%	13%	42%
Paraguay	60%	57%	33%
Peru	4%	68%	54%
Uruguay	35%	85%	88%
Average	30%	34%	54%

Notes: This table shows the fraction of prices denominated in US dollars on the online platform for each country and type of market (goods, vehicles, and real estate). For the goods market in Argentina, dollar pricing has not been allowed since 2012 (dollar pricing is still allowed for vehicles and real estate). In Brazil, Chile and Colombia (not included in the Table) price dollarization is zero due to explicit regulation.

the results broken down by vehicles, real estate, and consumer goods.[6] Table 2 presents correlations of price dollarization with households' asset dollarization, the inflation rate, exchange rate volatility, and the exchange rate pass-through to import prices. It is worth clarifying two points related to the cross-country analysis and its interpretation. First, although the availability of data for multiple economies is novel, the relatively small number of countries restricts our analysis to pairwise correlations. Thus, some of our correlations could be actually driven by a third common macro variable included or omitted in our analysis. Second, there might be feedback effects from price dollarization to the dynamics of these variables. Thus, we do not interpret these correlations as causal, but rather as evidence that is consistent with the model's predictions.

First, there is a high correlation between the share of prices in dollars and the average share of bank deposits that are denominated in dollars: countries with high levels of dol-

[6] The model is most applicable to the case of consumer goods and vehicles, and to a lesser extent, to real estate. The case of real estate has additional particularities since it is a market characterized by search frictions and the fact that units have their specific price attached to them. However, the main trade-offs that characterize currency choice in this model are also present in the case of real estate. In a previous version of this paper, Drenik and Perez (2018), we develop a model of currency choice in markets with search frictions that naturally generate time-to-sell, and show that most of the predictions of the theory carry through to that market.

larization in deposits tend to have higher levels of price dollarization. This high correlation is found in each of the three markets we analyze. This relationship is consistent with the prediction of Proposition 1, by which setting prices in dollars is more attractive when households have more wealth denominated in dollars, and constitutes a new fact that was not explored in the literature before.

Table 2: Price Dollarization: Cross-Country Correlations

	All (avg.)	Goods	Vehicles	Real Estate
Correlation with:				
Deposit Dollarization	71%	66%	64%	59%
Avg. Inflation (last 5 yrs)	20%	19%	-3%	35%
Avg. Inflation (last 20 yrs)	19%	11%	-4%	34%
NXR Volatility	-31%	-28%	-29%	-29%
Avg. Inflation-NXR Vol. Ratio	61%	69%	49%	48%
Import Prices Pass-through	11%	32%	-13%	15%
Trade Openness	30%	73%	16%	5%

Notes: This table presents the correlation between the share of prices that are denominated in dollars for each country and different macroeconomic variables. The first column presents the correlation with the average degree of price dollarization across markets. The rest of the columns present the correlation in the market of goods, vehicles, and real estate, respectively. Deposit dollarization is defined as the share of deposits denominated in US dollars. Average inflation corresponds to the average annual inflation rate of the last 5 and 20 years. Exchange rate volatility corresponds to the standard deviation of monthly changes in the dollar exchange rate. Import prices pass-through corresponds to the contemporaneous pass-through of the dollar exchange rate to the import price index. Trade openness is defined as the ratio of the sum of total exports and imports to GDP. Cross-country correlations are computed with data from 15 countries (those from Table 1 and Brazil, Chile and Colombia).

Second, we also analyze the cross-country relationship between price dollarization and inflation. Our theory predicts that countries with higher inflation rates should display higher shares of price dollarization. Empirically, we find a positive, albeit mild, relationship between these variables. The correlation of price dollarization with the average recent inflation (the average of the last 5 years) is 20%. Similar results are found when looking at historical levels of inflation (the average inflation in the last 20 years). This correlation is slightly stronger with price dollarization in the real estate market.

Price dollarization exhibits a stronger correlation with the volatility of the nominal exchange rate: countries with a more volatile exchange rate have a larger share of prices denominated in local currency. The correlation is -31% and similar across all markets. This relationship is consistent with the prediction of Proposition 1, by which dollar pricing is less likely when the variance of exchange rate shocks is higher. However, the theory also predicts that currency choice is determined by the ratio between inflation and the volatility of exchange rate shocks. The correlation between this ratio and price dollarization is much higher: it is 61% across markets and reaches 69% in the goods market.

Finally, we relate price dollarization with the model mechanisms associated with international trade. We compute the correlation between price dollarization and the pass-through of exchange rate to the import price index at the country level.[7] Our theory predicts that countries with higher exchange rate pass-through to import prices–which in the model correspond to the prices of the tradable input–should display higher shares of price dollarization. Empirically, we find a positive but small correlation. For the case of consumer goods, which are the type of goods for which the theory is most applicable, the correlation is 32%. A related prediction of the theory is that more tradable goods are more likely to be price in dollars. Here, we provide a first test of this prediction using aggregate data by computing the correlation between price dollarization and trade openness. We find a high correlation of 73% between these variables in the goods market: countries that are more open to international trade exhibit larger shares of prices set in dollars.

4.2 Price Dollarization at the Micro Level

In this section, we study the patterns of dollarization of prices at the micro level. We test two additional predictions of our theory by exploring the extent to which characteristics of the good and the seller are relevant in explaining the currency choice of prices. We perform this analysis for the four countries with the largest amount of data and with a positive share of dollar pricing in at least one market: Argentina, Mexico, Peru, and Uruguay.

We begin our analysis by conducting a variance decomposition of the currency choice of into variations across sellers and across broad type of goods. We define broad types of goods as those in the same branch of a category tree provided by the online platform. We provide more details related to the estimation of this variance decomposition in Appendix E. Both seller and good characteristics are relevant in explaining currency choices of prices. On average, seller fixed effects explain 36% of the variation in the currency choice of prices, and category fixed effects explain 21% (see Table E1). We next assess the role of two features of goods and sellers–the tradeability of the good and the sellers' size–in the determination of

[7] The pass-through is computed by regressing annual log changes of the import price index on annual log changes of the exchange rate vis-a-vis the US dollar. We use annual data to maximize the number of countries for which we can compute the pass-through.

the currency of prices.

Price Dollarization and Tradeability of Goods– In most countries, some types of goods exhibit higher levels of dollarization than others. Examples of relatively more dollarized goods include consumer electronics (e.g., mobile phones, digital cameras, smart TVs), home appliances (e.g. refrigerators, air conditioners), and vehicles. These types of goods tend to have a large imported content. On the other hand, examples of goods that tend to be posted in local currency include clothing and small gadgets, which tend to have a lower import content.

We examine whether more tradeable goods are more likely to be posted in dollars by assigning a tradeability index to each listing of goods included in the historical dataset of Argentina and Uruguay.[8] We do this in multiple steps. First, we merge trade data on imports with output data (at the 3-digit level of the ISIC classification) for the manufacturing sectors and compute a tradeability index for each sector, defined as the ratio of imports to the sum of imports and output. Second, we map the tradeability indices to the data from the online platform by matching manufacturing sectors to each category available in the category tree provided by the platform. This step requires matching manufacturing sectors to more than 30,000 categories in total. Finally, we assign to each listing the tradeability index that corresponds to the finest category of the listing. This procedure shows that there is substantial heterogeneity in tradeability across types of goods: clothing have low tradeability, while computers are highly likely to be imported. We describe the trade and output data, merging procedure, and tradeability indices in more detail in Appendix C.5.

Next, we group listings of goods of each country by their degrees of tradeability: low tradeability (those with tradeability indices in the first tercile), medium tradeability (those with tradeability indices in the second tercile) and high tradeability (those with tradeability indices in the third tercile). Columns (1) and (3) of Table 3 shows the share of listings posted in dollars for these three groups, which we compute by regressing the price dollarization dummy on tradeability terciles fixed effects. Goods that are more tradeable are more likely to be denominated in dollars. The increasing relationship is stronger in Uruguay than in Argentina. While the share of dollar prices is around 1% and 5% for low tradeability goods, this share increases to 20% and 36% in Argentina and Uruguay, respectively. This increasing

[8]For this particular analysis, we work with the historical dataset, since its time period (2003-12) includes the years for which we have industry-level data on exports, imports, and GDP.

relationship between price dollarization and tradeability is robust to the inclusion of seller fixed effects, as shown in columns (2) and (4).

These findings are consistent with the prediction in Proposition 1, according to which dollar pricing is more likely when the share of tradable inputs is larger. Since in these countries the prices of imported goods at the border tend to be set in US dollars (Gopinath, 2016), the costs of the tradable input of goods co-move more strongly with the exchange rate and firms prefer to set their retail prices in dollars.

One exception to this empirical pattern is the real estate market, which is non-tradable and heavily dollarized. In a previous version of this paper, Drenik and Perez (2018), we argue that this particular market is characterized by search frictions. There, we rationalize price dollarization by documenting that the average time a real estate unit is available for sale ranges between four and six months. This, coupled with the fact that inflation in local currency is significantly larger than in foreign currency, results in sellers choosing to price in dollars in the real estate market in order to avoid costs of changing prices frequently. Later, we will show that the currency choice of listed prices does matter in this market, by documenting that nominal exchange rates have a differential impact on the probability of leaving the platform (which we interpret as a sale) as a function of the currency of the price.

Table 3: Price Dollarization and Tradeability

	Argentina		Uruguay	
1st Tercile	0.011		0.047	
	(0.000)		(0.000)	
2nd Tercile	0.109	0.022	0.277	0.098
	(0.000)	(0.000)	(0.000)	(0.001)
3rd Tercile	0.197	0.043	0.362	0.145
	(0.000)	(0.000)	(0.001)	(0.001)
N	34003505	33792430	2555929	2516957
R^2	0.147	0.577	0.301	0.539
Seller FE	No	Yes	No	Yes

Notes: This table shows the share of prices set in dollars in Argentina and Uruguay, by tercile of the tradeability index. The tradeability index is computed as the ratio of sectoral imports to the sum of sectoral imports and output. The first column in each country estimates a linear probability model of price dollarization (0-1 dummy variable) on terciles of the tradeability index. The second column in each country estimates a similar model by including seller fixed effects.

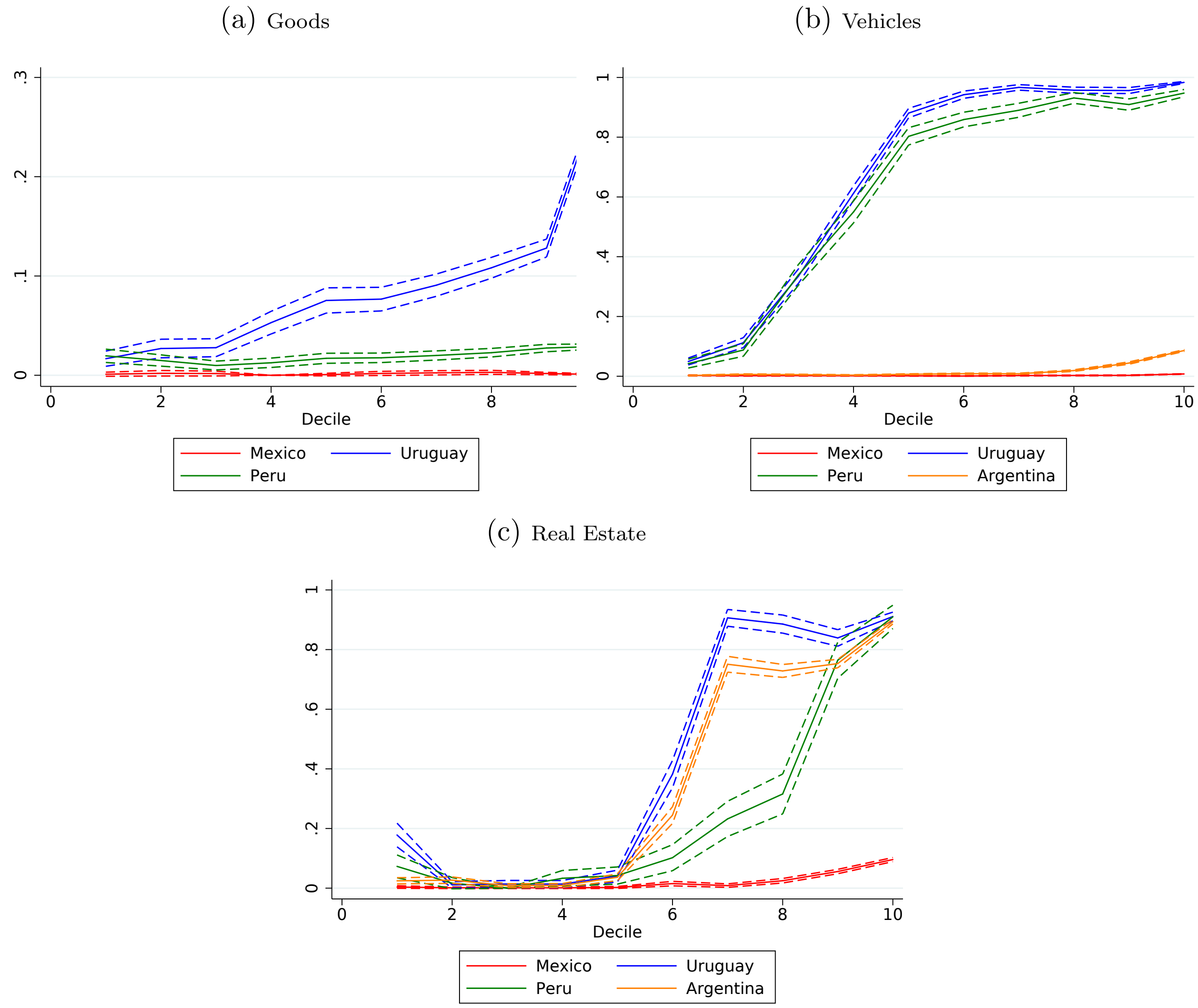
Price Dollarization and Size of Sellers– This section is motivated by the last theoretical prediction of Proposition 1, by which firms with larger debt dollarization are more likely to set prices in dollars. To test this prediction we would need data on firms' debt by currency, which is not available. However, prior research has found a strong empirical relationship between the size of the firm and the share of debt denominated in foreign currency (see, for example, Kamil, 2012; Licandro and Mello, 2019; Richers, 2019; Salomao and Varela, 2019). Therefore, to the extent that larger firms have larger debt dollarization, one can indirectly test the model's prediction by analyzing the relationship between the seller's size and the currency choice of prices.[9]

Figure 1 plots the point estimates of an OLS regression of a seller's share of revenues from listings posted in dollars on a categorical variable indicating the sellers' decile of total revenues in the same currency (Figure B.4 in the Appendix shows similar results when also including category fixed effects). In almost all countries and all broad types of goods, we observe an increasing relationship between the dollarization of revenues and the size of sellers. For example, only 1.6% of revenues of smallest sellers in the goods market in Uruguay come from goods posted in dollars. This figure rises above 20% for sellers in the top decile of the size distribution. Table B.6 in the Appendix shows higher shares of prices set in dollars for the top revenue-weighted tercile of the size distribution, which is more illustrative of price dollarization for the largest firms given the fat right tail of the distribution.

Finally, we examine whether sellers are likely to post goods in multiple currencies. We now focus on sellers with positive revenues and more than one listing, and split them into terciles of the revenue distribution, for each country and broad type of good. We compute the share of sellers that post goods in multiple currencies ("multi-currency sellers"). The last three columns of Table B.5 in the Appendix show the results. The share of multi-currency sellers in the goods market is 8%. This low share is consistent with the fact that seller fixed effects explain a large variation of the currency choice of prices. However, larger sellers are more likely to be multi-currency sellers. This last fact holds for almost all countries and broad types of goods.

[9] An alternative channel through which size can impact currency choice is through its markup elasticity (see, for example, Amiti et al., 2019). If the markup elasticity is increasing in the firm's size, then larger firms would find it more attractive to set prices in the local currency (which in their framework would correspond to the currency of destination).

Figure 1: Price Dollarization by Sellers' Size



Notes: The panels plot the point estimates of an OLS regression of a seller's share of revenues that correspond to listings posted in dollars on a categorical variable indicating the sellers' decile of total revenues. The dashed lines indicate 95% confidence intervals constructed with robust standard errors. We estimate one regression for each country and type of good. The sample is restricted to sellers with positive revenues from active listings during March-October 2018. For the goods market in Argentina, dollar pricing has not been allowed since 2012.

5 Currency Choice and Exchange Rate Pass-through

In this section, we analyze the empirical relationship between currency choice and exchange rate pass-through. We begin by documenting that prices are sticky and that the currency of prices determines the short-run pass-through of exchange rate movements to prices. Next, we estimate medium-run pass-through to prices and show that those estimates and firms' currency choice are aligned with the predictions of the theory stated in Proposition 1. Finally, we document that the currency of prices determines the short-run pass-through to quantities. This analysis suggests that exchange rate movements have allocative effects due to the presence of price dollarization.

5.1 Price Stickiness by Currency

Table E2 shows various summary statistics regarding price changes of goods, vehicles, and real estate in the main countries. We document significant heterogeneity across types of goods and also across countries. The frequencies of price changes range from 0.1% to 2.5% in most countries and types of goods. Large heterogeneity in the degree of price stickiness was previously estimated across countries (see, for example, Blanco and Cravino, 2020) and across sectors (see, for example, Nakamura and Steinsson, 2008). When comparing price stickiness by currency, we find that, with few exceptions, the frequency of price changes is larger for prices in local currency than for prices in dollars. Finally, changes in the currency of denomination of prices within listings are very rare (with average daily probabilities of a change in currency lower than 0.05%). In Appendix E, we provide further details on the analysis of price stickiness.

5.2 Short-Run Exchange Rate Pass-through to Prices

We now investigate the degree of pass-through of exchange rate movements to prices, depending on their currency of denomination. To pursue this analysis, we exploit the fact that we observe prices at a daily frequency for a period of 8 months (March to October 2018). In this section, we restrict attention to Argentina and Uruguay, which are the two main countries that exhibit large degrees of price dollarization and experienced significant movements in the nominal exchange rate during this time period (Figure B.5 shows the dynamics of the nominal exchange rate for these two economies).[10] The nature of the data and the time period of analysis thereby allows us to estimate pass-through at a high frequency in the short run.

We first study the degree of pass-through to individual prices. We estimate the following pass-through regression for each country and each type of market (goods, vehicles, and real

[10] In the other countries for which we have large amounts of data (Mexico and Peru), either the nominal exchange rate displayed small variations during the window of observation or the share of dollar prices is small. For these reasons, we cannot precisely estimate pass-through for these countries.

estate):

$$\Delta p_{i,j,t} = \alpha_j + \sum_{k=0}^{K} \beta_k^d \Delta e_{t-k} \times \mathbb{1}\{currency_i = d\} + \sum_{k=0}^{K} \beta_k^{lc} \Delta e_{t-k} \times \mathbb{1}\{currency_i = lc\} + \epsilon_{i,j,t}, \quad (5)$$

where i indexes the individual listing, j indexes the category of the good, t is calendar time (in days), α_j is a category fixed effect (to allow for category-specific average inflation rates), $\Delta p_{i,j,t}$ is the daily difference in log prices (expressed in domestic currency), Δe_t is the daily difference in the log nominal exchange rate (domestic currency per dollar), and $\mathbb{1}\{currency_i = d\}$ ($\mathbb{1}\{currency_i = lc\}$) is a dummy variable equal to one when the currency of the price is in dollars (local currency). We focus on short-run responses and set the number of lags K to 90 days; this choice is constrained by the relatively short time span of the data. We are interested in the cumulative pass-through for prices in local currency and in dollars at a horizon of n days, which are given by $\sum_{k=0}^{n} \beta_k^{lc}$ and $\sum_{k=0}^{n} \beta_k^{d}$, respectively.

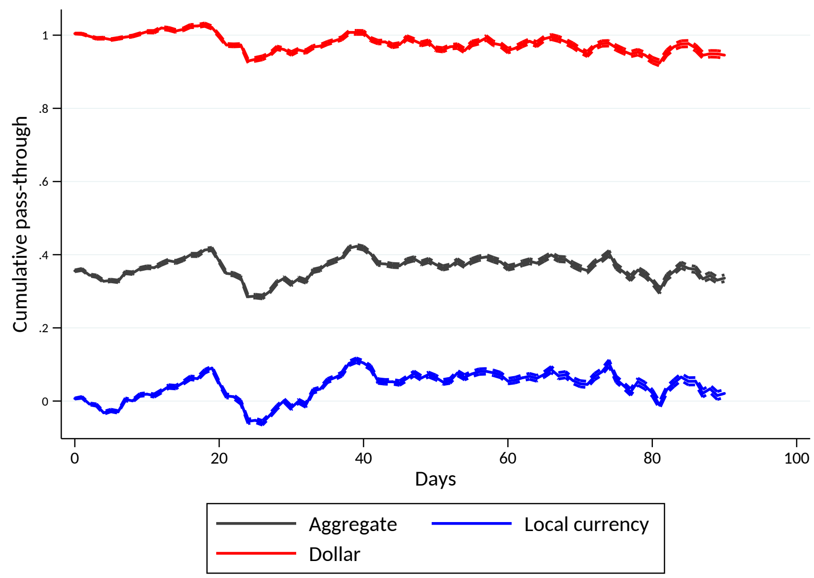
Figure 2a shows pass-through estimates to prices of goods in Uruguay. Each solid line reports the estimates of $\sum_{k=0}^{n} \beta_k^{cur}$ for $cur = lc, d$, and the dashed lines correspond to their 95% confidence intervals (standard errors are clustered at the listing level), as a function of the number of lags n on the horizontal axis. We also include pass-through estimates when we restrict these to be the same across currencies. The pass-through is close to zero for prices in local currency and close to one for prices in dollars. After 90 days, the majority of the difference in pass-through across currencies persists. This is consistent with the measured degree of price stickiness. Similar estimates are obtained for Argentina and Uruguay in the markets for vehicles and real estate (see Figures B.6 and B.7). These results are consistent with the findings of Gopinath et al. (2010), and suggest that in the short-run shocks in the exchange rate convert almost one for one into shocks to relative prices of those goods posted in different currencies.

5.3 Medium-Run Exchange Rate Pass-through to Prices

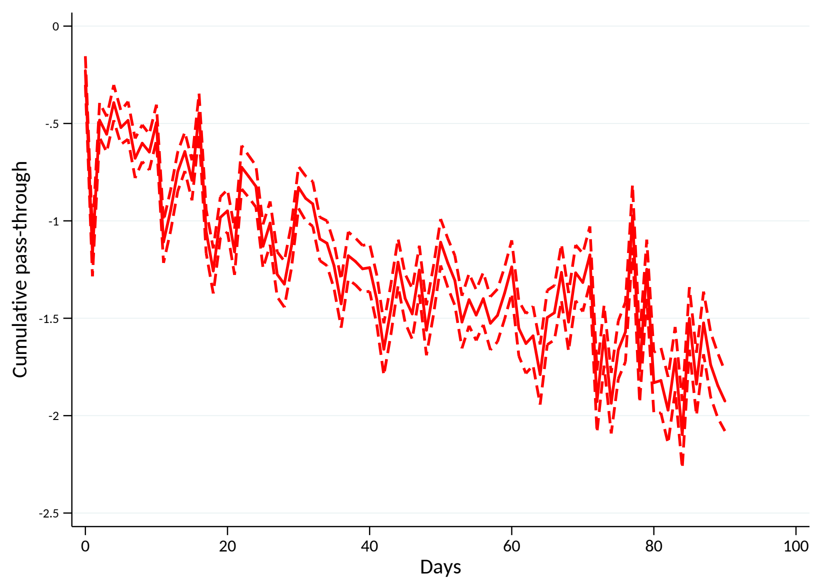
In Section 2, we show that there exists a sufficient statistic for MRPT that can be estimated with available data. Here, we provide estimates of the sufficient statistic and show that the empirical evidence supports the model's predictions regarding currency choice. We proceed

Figure 2: Exchange Rate Pass-through to Prices and Quantities

(a) Exchange Rate Pass-through to Prices



(b) Exchange Rate Pass-through to Quantities



Notes: These figures show the estimated pass-through to prices (in Panel 2a) and quantities (in Panel 2b) for Uruguay in the goods market. Panel 2b presents estimates of pass-through to quantities sold of listings posted in dollars relative to quantities sold of listings posted in local currency. Dashed lines correspond to 95% confidence intervals (standard errors are clustered at the listing level).

by estimating

$$\Delta\bar{p}_{i,j,t} = \alpha_j + \beta^d \Delta_c e_{i,j,t} \times \mathbb{1}\{currency_i = d\} + \beta^{lc} \Delta_c e_{i,j,t} \times \mathbb{1}\{currency_i = lc\} + \epsilon_{i,j,t}, \quad (6)$$

where i indexes the individual listing, j indexes the category of the good, t is calendar time (in days), α_j is a category fixed effect, $\Delta\bar{p}_{i,j,t}$ is the change in log prices (expressed in domestic currency) *conditional on a price change*, $\Delta_c e_{i,j,t}$ is the cumulative change in the log nominal exchange rate (domestic currency per dollar) over the duration of the previous price, and $\mathbb{1}\{currency_i = d\}$ ($\mathbb{1}\{currency_i = lc\}$) is a dummy variable equal to one when the currency of the price is in dollars (local currency).[11] The coefficients of interest are β^d and β^{lc}, which estimates the pass-though conditional on a price change.

Table 4: Pass-Through Conditional on Price Change

	Dollar		Non-Dollar			MRPT	Price
Country	β^d	S.E.	β^{lc}	S.E.	N	Cutoff	Dollarization
Goods							
Uruguay	1.07	(0.03)	0.24	(0.01)	225569	0.42	35%
Vehicles							
Argentina	0.85	(0.01)	0.35	(0.00)	362707	0.42	9%
Uruguay	0.97	(0.05)	0.06	(0.25)	12065	0.46	85%
Real Estate							
Argentina	0.88	(0.00)	0.46	(0.01)	45691	0.37	76%
Uruguay	0.96	(0.05)	0.06	(0.09)	15871	0.44	88%

Notes: This table reports the estimated pass-through to prices for Argentina and Uruguay. The first panel reports estimates for the goods market, the second panel for the vehicles market, and the last panel for the real estate market. The first four columns report the point estimates and standard errors for listings priced in dollars and local currency. The fifth column reports the number of observations and the R^2. Each regression is estimated with OLS. Standard errors are clustered at the listing level. The sixth column reports the cutoff value for MRPT derived in Proposition 1. This cutoff is computed with country-specific observed inflation and volatility of nominal exchange rate, country-market-specific price stickiness, and annualized discount factor of 0.96. In the market for real estate, we adjust the discount factor to take into account the fact that the seller's objective is to sell a single unit of real estate, which occurs in 5 months on average. The last column reports the share of prices in dollars.

Table 4 reports the OLS estimates of equation (6) for Argentina and Uruguay, and all markets. The first four columns report the estimates and their standard error (clustered at the listing level), and the fifth column reports the number of observations. In the goods market in Uruguay, the exchange rate pass-through conditional on a price change is 1.07 ($S.E. = 0.03$) for prices denominated in dollars and 0.24 ($S.E. = 0.01$) for prices denominated in local currency. A wider gap is observed in the market for vehicles and real estate. A similar

[11] The sufficient statistic of Lemma 2 in the Appendix is based on a regression of $\Delta\bar{p}_{i,j,t}$ on $\Delta e_{i,j,t} = e_{i,j,t} - e_{i,j,t-1}$. We follow the regression specification in Gopinath et al. (2010), who show that in a calibrated model both specifications yield similar results.

pattern is found in Argentina, but the difference in pass-through conditional on a price change across currencies is smaller due to a larger pass-through to prices in local currency.

Proposition 1 predicts that firms choose dollar (local currency) pricing if MRPT is above (below) the cutoff $\frac{1}{2}\left(1-\left(\frac{1}{1-\rho\theta}\right)\frac{\mu^2}{\textsc{Var}(\epsilon_e)}\right)$. We compute this cutoff for each country and market using data on country daily inflation and the variance of daily changes in the nominal exchange rate, as well as country-market specific estimates of the daily probability of a price change. The only parameter that is not measurable is the discount factor, which we set to $\rho = 0.96^{(1/365)}$ (results are robust to alternative discount factors). The cutoffs, reported in column six of Table 4, are lower than 0.5 due to the presence of inflation, and exhibit heterogeneity across countries and markets, due to differential degrees of price stickiness. Consistent with the theory, the estimated MRPT for dollar prices is always above the cutoff, whereas the estimated MRPT for local currency prices is below the cutoff, with the exception of real estate in Argentina. To provide additional validation of the model presented in Section 2, Table B.7 takes advantage of differences in the degree of prices stickiness across more disaggregated definitions of categories and compares estimates of MRPT across category-currency pairs with their respective cutoffs. Results show that the theory has a high predictive power (between 70% and 80%) of the currency of invoicing across narrowly defined categories.

5.4 Exchange Rate Pass-through and Quantities

We now focus on a more novel aspect of the analysis: whether changes in relative prices generated by movements in the exchange rate differentially affect quantities sold. For each listing, we observe the quantities sold at a daily frequency. These data allow us to estimate whether a nominal exchange rate depreciation, which in the short run renders goods posted in dollars more expensive relative to those in local currency, induces a negative effect on relative quantities sold for goods priced in dollars. That is, with these data we are able to estimate the short-run elasticity of demand using movements in the nominal exchange rate as shocks to the relative prices of goods. To estimate these elasticities, we estimate the following regression for each country and each type of good:

$$\Delta q_{i,j,t} = \alpha_{j,t} + \sum_{k=0}^{K} \theta_k \Delta e_{t-k} \mathbb{1}\{currency_i = d\} + \epsilon_{i,j,t}, \tag{7}$$

where $\Delta q_{i,j,t}$ is the daily difference in log quantities sold in the case of goods, and the absolute change in the case of vehicles and real estate (in these markets listings advertise a single unit, then daily quantity sold is either zero or one). Thus, we estimate an elasticity in the goods market and a semi-elasticity in the other two markets. We include category-time fixed effects and measure categories of good j at level 3 in the category tree. This is a fine categorization that corresponds to goods that are close substitutes. Examples of these categories include Apple smart-watches, soccer jerseys, strollers, wallets and Playstation 4 (see Table B.4 for further examples). The inclusion of these fixed effects implies that we are estimating the differential response to exchange rate movements across currency of denomination of prices within types of goods.

In Appendix F, we show how the estimate of $\sum_{k=0}^{K} \theta_k$ in specification (7) corresponds to an estimate of the elasticity of demand from a nested CES structure in which each nest corresponds to a category j. Two key features enable us to estimate this structural elasticity. First, the finding that prices are sticky in the short-run and pass-through is complete for prices in dollars and zero for prices in local currency implies that a shock to the exchange rate corresponds to a shock of equal magnitude to the price of goods in dollars relative to goods in local currency. Second, the inclusion of category-time fixed effects $\alpha_{j,t}$ in specification (7), which capture any shifts in category-specific demand that are due to movements in exchange rates or any other aggregate shocks.

Figure 2b shows the estimation results for the goods market in Uruguay. The solid line reports the estimates of $\sum_{k=0}^{K} \theta_k$ and the dashed lines their 95% confidence intervals (standard errors are clustered at the listing level), as a function of the number of lags n on the horizontal axis. The estimated cumulative elasticity after a month is close to -1, and after 90 days it is close to -1.85. The magnitude of this short-run elasticity is in line with estimated short-run elasticities for durable goods in the IO literature. For example, Gowrisankaran and Rysman (2012) estimate the own price elasticity to be in the range of -1.2 to -2.6, depending on whether the price change is temporary or not and whether the price change is industry-wide or not. In the markets of vehicles and real estate, the estimated three-month semi-elasticities range between -0.8 and -5 for Argentina and Uruguay (see Figures B.6 and B.7), respectively. These semi-elasticities are economically relevant. After a 1% devaluation of the exchange rate, the relative probability of a sale within three months in the market for vehicles in Uruguay declines by 13% of the average quarterly sale probability for listings priced in dollars. In standard New Keynesian models, changes in prices have immediate effects on quantities. However, we see that in all cases the estimated cumulative pass-through is increasing over time. These delays could be due to search frictions or the fact that purchases of durable goods are staggered over time, so the effects accumulate over time. Finally, we also estimate specification (7) for prices instead of quantities, and find estimates that are close to the difference between the pass through in dollars and local currency, estimated in specification (5) (see Figures B.8 and B.9).

These findings point to a strong role of the currency of prices in determining the degree of pass-through of exchange rate shocks to prices. This is stressed in the previous literature for the case of import and export prices at the dock. Here, we argue that similar results are obtained in retail markets of emerging economies that display price dollarization. Additionally, our findings on quantities show that nominal exchange rate shocks have an effect on quantities sold and economic activity through their effect on prices. Thus, sellers' currency choices are not only relevant for the degree of pass-through to prices, but also for the effects of nominal exchange rate shocks on real allocations in the short run. This effect of exchange rate shocks on quantities via prices is implicitly assumed in every theory of endogenous currency choice (including our model), and here we provide direct evidence for it.

6 Relevance for Broader Aggregates

In this section, we argue that the currency of prices has relevant implication for the macroeconomy by showing that the incidence of dollar pricing in the micro data from the online platform is a strong predictor of the degree of pass-through in the CPI data. We do this by comparing aggregate and market-specific pass-through across countries, and also across fine types of goods within a particular country. Our results imply that price dollarization is also relevant for broader aggregates such as the dynamics of the aggregate CPI.

6.1 Country-level analysis

We estimate country-specific pass-through to aggregate prices and analyze whether it correlates with the degree of price dollarization across countries. To compute pass-through, we estimate for each country in our sample the following regression:

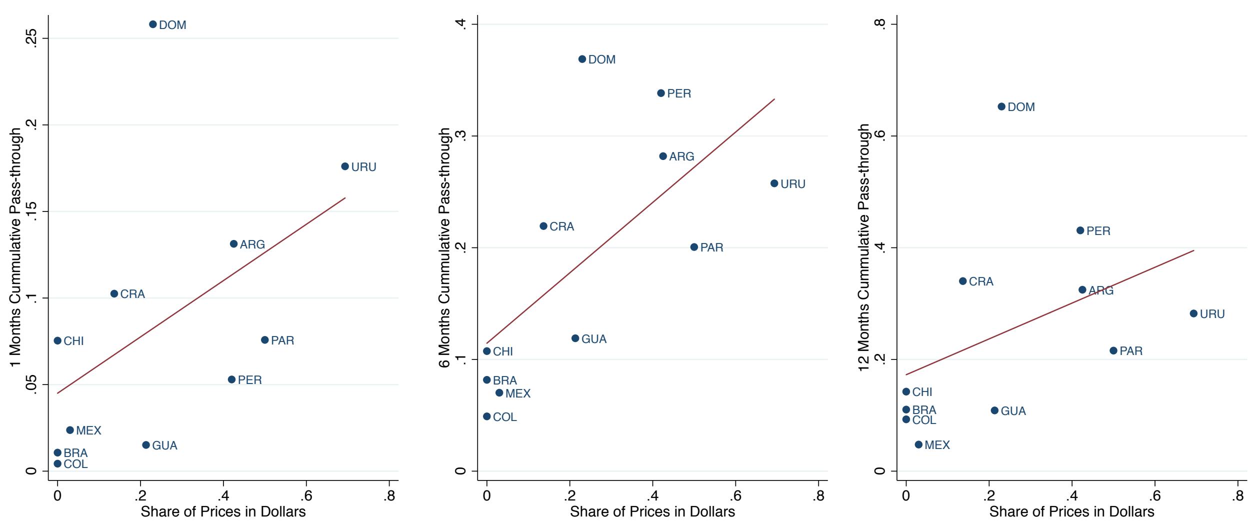
$$\pi_{c,t} = \alpha_c + \sum_{k=0}^{24} \beta_{c,k} \Delta e_{c,t-k} + \sum_{k=0}^{24} \gamma_{c,k} \pi_{US,t-k} + \sum_{k=0}^{3} \delta_{c,k} \Delta y_{c,t-k} + \epsilon_{c,t}, \tag{8}$$

where c indexes the country, t is calendar time (months), π is aggregate domestic CPI inflation, Δe is the difference in the log nominal exchange rate (domestic currency per dollar), π_{US} is aggregate CPI inflation in the US, and Δy is GDP growth. The number of lags is 24 months for the nominal exchange rate and the US inflation rate, and 3 months for GDP growth.[12]

Figure 3 shows the estimated cumulative pass-through at the 1-, 6-, and 12-month horizon—which at horizon n is given by $\sum_{k=0}^{n} \beta_{c,k}$—and the share of prices in dollars for all countries in our sample. As indicated by the line of best fit, there is a strong positive relationship between the degree of pass-through at all horizons and the share of prices in dollars, with correlations that range between 40% and 70%. These differences are consistent with results from the previous section that show that the short-run pass-through to prices is equal to one for prices set in dollars, and zero for prices set in local currency.

Figure 3: Price Dollarization and Pass-Through: Cross-Country Evidence

(a) 1M Pass-through (b) 6M Pass-through (c) 12M Pass-through



Notes: These figures plot estimates of exchange rate pass-through for each country in our sample, as a function of the degree of price dollarization computed with data from the online platform. Panels (A), (B) and (C) present estimates at the 1-, 6- and 12-month horizon, respectively. The red line is the best linear fit of the point estimates.

[12] We estimate the same specification as Gopinath et al. (2010), with the same number of lags. The sample period used for this estimation is 1990-2018. For those countries whose data starts after 1990, we use all available data. We exclude Bolivia, Honduras, Nicaragua, and Panama from this analysis, since they have or have had a fixed exchange rate with the dollar for most of the past 20 years. We provide more details on data used for the regressions in Appendix C.

Additional results Figure B.10 in the Appendix shows the dynamics of the estimates of $\sum_{k=0}^{n} \beta_{g,k}$ for three groups of economies (those with zero, low, and high dollarization), as a function of the number of lags n on the horizontal axis. The cumulative pass-through in high-dollarization economies is higher than that of non-dollarized economies at all horizons. The on-impact pass-through is 0.14 in high-dollarization economies compared to 0.02 in non-dollarized economies, and the pass-through after 2 years is 0.46 and 0.17, respectively.

Finally, we argue that this positive relationship also persists when we focus on the cross-country variation for each broad type of good. For this, we construct aggregate price indices for goods, vehicles and real estate for each country. We then estimate the pass-through for each country-market pair in our sample, and analyze whether these correlate with the degree of price dollarization across countries for each broad type of good. Table B.8 in the Appendix reports the correlation between the share of prices in dollars and the degree of pass-through at different horizons, for goods, vehicles and real estate. These correlations are positive in all cases and particularly strong for vehicles and real estate.

6.2 Good-level analysis

One potential concern associated with the previous cross-country analysis is that results could be driven by a third common factor (for example, monetary policy), that jointly affects price dollarization and CPI pass-through. To alleviate such concern we perform a complementary within-country analysis by examining the relationship between exchange rate pass-through and the degree of price dollarization for different good categories of the CPI.

Our analysis uses CPI price data on narrowly defined categories of goods, and data on the incidence of dollar pricing from the online platform, both for the case of Uruguay. We obtained disaggregated data on more than 300 categories of goods that are part of the CPI at a monthly frequency for the period 1997-2010. Examples of these categories include digital cameras, glasses, tennis shoes, jeans, and mattresses. We then estimate the same regression specification as in (8) for each good category, and obtain good-specific pass-through estimates. We also estimate the fraction of prices set in dollars for each category in the CPI. Since the CPI data do not include the currency of denomination of prices, we use historical data from the online platform. For each category in the CPI, we identified whether there was a category in the online platform's category tree that corresponds to the same type of good. Approximately one-third of the categories in the CPI had a match in the data from the online platform. For those matched categories, we compute the fraction of prices set in dollars for all transactions of goods in the corresponding categories of the online platform.

We then assess the relationship between the estimated pass-through and the share of dollar prices for each matched category of the CPI. Results are shown in Figure 4, which plots the estimated cumulative pass-through at 1-, 6-, and 12-month horizons and the share of prices in dollars for each category. As shown by the fit of a local linear regression in each of the panels, there is an increasing relationship between pass-through and the share of prices denominated in dollars. The on-impact pass-through is close to zero for those goods with a negligible share of dollar prices, and close to one for those goods with a high share of dollar prices (Figure 4a).[13] For longer time horizons the relationship gradually flattens, as the pass-through of goods that are almost exclusively priced in local currency increases. However, even 1 year after the exchange rate shock, there are still significant differences in the pass-through of goods with different shares of dollar prices.

This analysis provides external validity for the results found using data from the online platform. The fact that we find a close relationship between the share of prices in dollars in the online platform and the pass-through of goods in the CPI data further suggests that price data from the online platform are relevant for broader aggregates, such as the dynamics of the aggregate CPI.

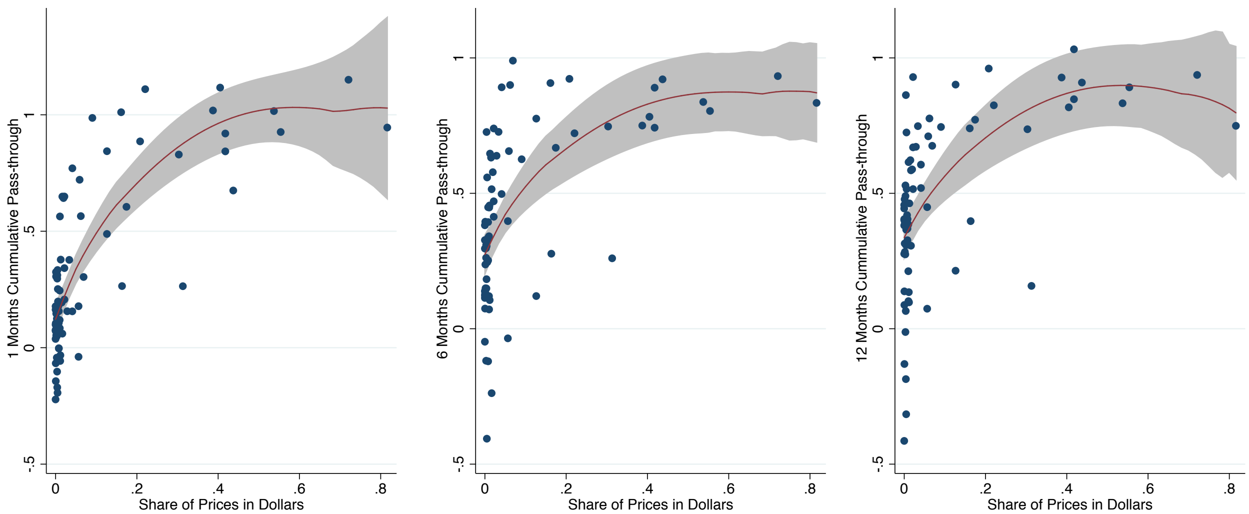
7 Conclusion

This paper provides an empirical investigation of the currency denomination of prices in various Latin American economies, through the lens of a model of currency choice of prices in domestic markets. Consistent with the model's predictions, there is extensive selection in currency choice of prices, both at the micro and the macro level. At the micro level, we show that larger sellers are more likely to post prices in dollars and that goods that are more tradeable are more likely to be posted in dollars. At the macro level, the use of dollars when pricing goods is strongly linked to the degree of asset dollarization and the ratio of average inflation to exchange rate volatility in an economy, and weakly linked to the pass-through

[13] Estimates of on-impact pass-through can be different to the share of prices in dollars for two reasons: (1) the adjustment of prices denominated in local currency, and (2) the time period for which we have data on price dollarization from the platform is more recent than the time period of the CPI data (on the platform, price dollarization has been slowly decreasing over time).

Figure 4: Price Dollarization and Pass-through: Product Level

(a) 1M Pass-through (b) 6M Pass-through (c) 12M Pass-through



Notes: These figures plot estimates of exchange rate pass-through using price indices of disaggregated products from Uruguay, as a function of the degree of price dollarization computed with data from the online platform. Panels (A), (B) and (C) present estimates at the 1-, 6- and 12-month horizon, respectively. The red line is the nonlinear fit of the point estimates from a local linear regression and the gray bands show 95% confidence intervals. The sample includes goods that are present both in the CPI and the online platform. The category all corresponds to the correlation between the average share of prices in dollars (computed as the average between goods, vehicles and real estate), and aggregate pass-through estimated with aggregate CPI data.

to import prices. This result calls for further development of theories that provide a unified framework to think about the use of the dollar fulfilling multiple roles of money (as in, for example, Gopinath and Stein, 2018) and theories that account for the wider use of dollars (as in, for example, Mukhin, 2018; Drenik et al., 2021).

Our paper also argues that the currency of denomination of prices is relevant for determining the degree of pass-through of nominal exchange rate shocks to both prices and quantities in retail markets. This result highlights the value of introducing dollar pricing in sticky-price models of small open economies to study the macroeconomic transmission of aggregate shocks as in, for example, Gopinath et al. (2020).

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ONLINE APPENDIX FOR *"PRICING IN MULTIPLE CURRENCIES IN DOMESTIC MARKETS"*

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A Model Details and Proofs

In this appendix, we provide further details on the model and the proofs of the proposition in the main body.

A.1 Model details

Firm's cost minimization problem– The cost minimization problem faced by the firms is given by:

$$\mathcal{C}(y) \equiv \min_{Y_{it}^T, Y_{it}^N} \left(P_t^T Y_{it}^T + P_t^N Y_{it}^N\right)(1+\nu i_t)$$

subject to

$$\left(\left(Y_{it}^T\right)^{\eta}\left(Y_{it}^N\right)^{1-\eta}\right)^{\gamma} = y.$$

The solution to this problem is given by (2). The flexible price that maximizes flow profits solves

$$\max_{P_{it}} P_{it}\frac{W_t}{P_t^{\text{cpi}}}\left(\frac{P_{it}}{P_t^{\text{cpi}}}\right)^{-\sigma} - \left(\frac{P_t^T}{\eta}\right)^{\eta}\left(\frac{P_t^N}{(1-\eta)}\right)^{1-\eta}(1+\nu i_t)\left(\frac{W_t}{P_t^{\text{cpi}}}\left(\frac{P_{it}}{P_t^{\text{cpi}}}\right)^{-\sigma}\right)^{1/\gamma}.$$

The solution to this problem is given by

$$\tilde{P}_{it} = \left(\frac{\sigma}{\gamma(\sigma-1)}\left(\frac{P_t^T}{\eta}\right)^{\eta}\left(\frac{P_t^N}{(1-\eta)}\right)^{1-\eta}(1+\nu i_t)\left(\frac{W_t}{P_t^{\text{cpi}}}\left(\frac{1}{P_t^{\text{cpi}}}\right)^{-\sigma}\right)^{1/\gamma-1}\right)^{\frac{1}{1-\sigma+\frac{\sigma}{\gamma}}}. \tag{9}$$

Given our demand structure, the optimal flexible price is non-decreasing in the prices of inputs, the interest rate and the wealth of households. Taking a log-linear approximation to this price we obtain

$$\tilde{p}_{it} \simeq k + \frac{\eta}{1-\sigma+\frac{\sigma}{\gamma}}p_t^T + \frac{1-\eta}{1-\sigma+\frac{\sigma}{\gamma}}p_t^N + \frac{\nu}{1-\sigma+\frac{\sigma}{\gamma}}i_t + \frac{1/\gamma-1}{1-\sigma+\frac{\sigma}{\gamma}}w_t + \frac{(\sigma-1)(1/\gamma-1)}{1-\sigma+\frac{\sigma}{\gamma}}p_t^{\text{cpi}} \tag{10}$$

where the constant is given by $k = \log(\sigma) - \log(\sigma-1) - \log(\gamma) - \eta\log(\eta) - (1-\eta)\log(1-\eta)$.

Firm's price setting problem– The value of a firm that has a log price p_L in local currency is given by

$$V_{Lt}\left(p_L\right) = \Pi_t(p_L) + \rho\theta\mathbb{E}_t\left[V_{Lt+1}\left(p_L\right)\right] + \rho\left(1-\theta\right)\mathbb{E}_t\left[V_{t+1}\right], \tag{11}$$

where $0 < \rho < 1$ is the discount factor, $V_{Lt+1}\left(p_L\right)$ is the firm's continuation value if the firm cannot adjust its price in the next period, and V_{t+1} is the continuation value if the firm can adjust the price and currency.[14] Similarly, the value of a firm that set a log price p_F in foreign currency is given by

$$V_{Ft}\left(p_F\right) = \Pi_t(p_F + e_t) + \rho\theta\mathbb{E}_t\left[V_{Ft+1}\left(p_F + e_{t+1}\right)\right] + \rho\left(1-\theta\right)\mathbb{E}_t\left[V_{t+1}\right], \tag{12}$$

where e_t is the log of the exchange rate, expressed as units of domestic currency per foreign currency.

We can also define the optimal prices in local and foreign currency, when firms have the opportunity to adjust their prices, as

$$\overline{p}_{ct} = \arg\max V_{ct}(p_{ct}), \tag{13}$$

for $c = L, F$. Finally, the firm's value of resetting its price and currency is given by $V_t = \max\left\{V_{Lt}\left(\overline{p}_{Lt}\right), V_{Ft}\left(\overline{p}_{Ft}\right)\right\}$.

Optimal currency and price choices– We now characterize the optimal price and currency choices. The following lemma generalizes familiar results on price and currency choices to inflationary settings.

LEMMA **1.** *Up to a first order approximation, the optimal prices in local and foreign currency satisfy*

$$\overline{p}_{Lt} - \left(\overline{p}_{Ft} + e_t\right) = \mu\frac{\rho\theta}{1-\rho\theta}.$$

Additionally, up to a second order approximation, the difference in the value of pricing in

[14] Given the symmetry between firms, we suppress the dependence of values and prices on i. Additionally, we make explicit the dependence of profits, $\Pi_t(p)$, on the log of the price expressed in local currency and on the period of time t. The subindex t indicates the dependence of the value functions on all the additional relevant information, other than the price.

local and foreign currencies is given by

$$\mathcal{L}_t \equiv V_{Lt}\left(\overline{p}_{Lt}\right) - V_{Ft}\left(\overline{p}_{Ft}\right)$$
$$\simeq \sum_{s=0}^{\infty} (\rho\theta)^s \left(-\mu^2 \left(\frac{\rho\theta}{1-\rho\theta} - s \right)^2 + \text{Cov}_t\left(e_{t+s}, e_{t+s} - 2\tilde{p}_{t+s}\right) \right).$$

Thus, a firm chooses to set prices in local currency if and only if

$$\frac{1}{2}\left(1 - \left(\frac{1}{1-\rho\theta}\right)\frac{\mu^2}{\text{Var}\left(\epsilon_e\right)}\right) > (1-\rho\theta)^2 \sum_{s=1}^{\infty} (\rho\theta)^{s-1} s \frac{\text{Cov}_t\left(e_{t+s}, \tilde{p}_{t+s}\right)}{\text{Var}_t\left(e_{t+s}\right)} \equiv MRPT. \tag{14}$$

Proof. See Section A.2. □

The first result characterizes the optimal choice of prices in both currencies. When there is positive inflation ($\mu > 0$), the reset price in local currency is higher than that in foreign currency. The reason is that inflation erodes the real value of nominal prices in local currency, but not the value of prices in foreign currency. This is because the local currency value of foreign currency prices increases with the exchange rate, which on average depreciates at the rate of inflation. Firms take this into account and set higher prices in local currency (compared to those in foreign currency) so that, on average, the real value of the price is not too distant from the optimal flexible price during the period of price stickiness.

The second result states that the currency choice depends on an inflation and a covariance component, denoted as the medium-run pass-through (MRPT). The inflation component is new to the analysis, whereas the MRPT component is already known from the literature and is still present in our extended setting. The firm will choose to set prices in foreign currency if the desired MRPT is greater than a cutoff value that is decreasing in inflation. This implies that higher inflation rates (or higher deflation rates) makes foreign currency pricing more attractive. The reason is that foreign currency pricing is a way of indexing prices to inflation. The higher the inflation rate, the larger the erosion of local currency prices relative to foreign currency prices, and the larger the incentives to choose the foreign currency. According to the covariance component, foreign currency pricing is more attractive when the optimal flexible price (9) covaries positively with the exchange rate. When $\mu = 0$, we recover the results in Gopinath et al. (2010), whereby currency choice is exclusively determined by desired medium-run pass-through being greater or lower than one half.

To test the main prediction of the theory, one needs to estimate $MRPT$. One of the main insights of Gopinath et al. (2010) is to show that there exists a sufficient statistic for MRPT that only requires available data. We show that this sufficient statistic is still valid in our modified setup. Let $\Delta_\tau \bar{p}_t$ denote the change of a price (in local currency) between time t and the time of the last adjustment $t-\tau$. Similarly, let Δe_t denote the change in the nominal exchange rate between time t and $t-1$.

Lemma **2.** *A regression of $\Delta_\tau \bar{p}_t$ on Δe_t provides a consistent estimate of MRPT.*

Proof. See Section A.3. □

Thus, a broad way to test the prediction of the model for domestic currency choice is to estimate MRPT for goods priced in local and foreign currency, and compare them with the cutoff that depends on the discount factor, and other observable data. We should expect to estimate a larger MRPT for goods priced in foreign currency. We perform such comparison in Section 5 of the paper.

A.2 Proof of Lemma 1

We start by showing the first result that characterizes optimal price choices. The first order conditions of the recursive problems (11) and (12) are given by

$$\sum_{s=0}^{\infty} (\rho\theta)^s \, \mathbb{E}_t \left[\Pi_{pt+s}(\overline{p}_{Lt})\right] = 0,$$
$$\sum_{s=0}^{\infty} (\rho\theta)^s \, \mathbb{E}_t \left[\Pi_{pt+s}(\overline{p}_{Ft} + e_{t+s})\right] = 0,$$

where we denote by Π_{pt} the first derivative of $\Pi_t(p)$. Taking a first order approximation of $\Pi_{pt+s}(p)$ evaluated at $\tilde{p}_{t+s}$, we can express

$$\Pi_{pt+s}(p) \simeq \Pi_{ppt}(\tilde{p}_t) \left(p - \tilde{p}_{t+s}\right).$$

Note that we also approximate state $t+s$ with state t. Using this approximation we can re-express the first order conditions as

$$\sum_{s=0}^{\infty} (\rho\theta)^s \, \mathbb{E}_t \left[\overline{p}_{Lt} - \tilde{p}_{t+s}\right] = 0, \tag{15}$$

$$\sum_{s=0}^{\infty} (\rho\theta)^s \, \mathbb{E}_t \left[\overline{p}_{Ft} + e_{t+s} - \tilde{p}_{t+s}\right] = 0. \tag{16}$$

Finally, we combine (15) and (16), and take expectations of future exchange rate to obtain $\overline{p}_{Lt} - (\overline{p}_{Ft} + e_t) = \mu\frac{\rho\theta}{1-\rho\theta}$.

Now we show the second result of the lemma. Consider now the difference between the value of setting optimal prices in local currency and the value of setting optimal prices in foreign currency

$$\begin{aligned} \mathcal{L}_t &= V_{Lt}\left(\overline{p}_{Lt}\right) - V_{Ft}\left(\overline{p}_{Ft}\right) \\ &= \sum_{s=0}^{\infty} (\rho\theta)^s \, \mathbb{E}_t \left[\Pi_{t+s}\left(\overline{p}_{Lt}\right) - \Pi_{t+s}\left(\overline{p}_{Ft} + e_{t+s}\right)\right]. \end{aligned} \tag{17}$$

Taking a second order approximation of the profit function evaluated at optimal flexible price yields

$$\Pi_{t+s}(p) \simeq \Pi_{t+s}\left(\tilde{p}_{t+s}\right) + \frac{1}{2}\Pi_{ppt}\left(\tilde{p}_{t+s}\right)\left(p - \tilde{p}_{t+s}\right)^2, \tag{18}$$

where Π_{ppt} refers to the second derivative of $\Pi_t(p)$. It can be shown that $\Pi_{ppt}\left(\tilde{p}_{t+s}\right) < 0$. Substituting (18) into (17) we obtain

$$\begin{aligned} \mathcal{L}_t &\simeq \frac{\Pi_{ppt}\left(\tilde{p}_{t+s}\right)}{2} \sum (\rho\theta)^s \, \mathbb{E}_t \left[\left(\overline{p}_{Lt} - \tilde{p}_{t+s}\right)^2 - \left(\overline{p}_{Ft} + e_{t+s} - \tilde{p}_{t+s}\right)^2\right] \\ &= \frac{\Pi_{ppt}\left(\tilde{p}_{t+s}\right)}{2} \sum (\rho\theta)^s \, \mathbb{E}_t \left[\left(e_t + \mu\frac{\rho\theta}{1-\rho\theta} - e_{t+s}\right)\left(\overline{p}_{Lt} + \overline{p}_{Ft} + e_{t+s} - 2\tilde{p}_{t+s}\right)\right], \end{aligned} \tag{19}$$

where in the second line we used the first result of lemma 1. We can re-express the conditional expectation as

$$\begin{aligned} &\mathbb{E}_t \left[\left(e_t + \mu\frac{\rho\theta}{1-\rho\theta} - e_{t+s}\right)\left(\overline{p}_{Lt} + \overline{p}_{Ft} + e_{t+s} - 2\tilde{p}_{t+s}\right)\right] = \\ &\mathbb{E}_t \left[e_t + \mu\frac{\rho\theta}{1-\rho\theta} - e_{t+s}\right] \mathbb{E}_t \left[\overline{p}_{Lt} + \overline{p}_{Ft} + e_{t+s} - 2\tilde{p}_{t+s}\right] - \mathrm{Cov}_t\left(e_{t+s}, e_{t+s} - 2\tilde{p}_{t+s}\right). \end{aligned} \tag{20}$$

Finally, we use (10), together with the assumed exogenous processes, to compute the two conditional expectations above:

$$\mathbb{E}_t\left[e_t+\mu\frac{\rho\theta}{1-\rho\theta}-e_{t+s}\right]\mathbb{E}_t\left[\overline{p}_{Lt}+\overline{p}_{Ft}+e_{t+s}-2\tilde{p}_{t+s}\right]=\mu^2\left(\frac{\rho\theta}{1-\rho\theta}-s\right)^2. \tag{21}$$

Substituting (20)-(21) into (19) yields our result.

A.3 Proof of Lemma 2

We begin the proof by showing what the outcome of an OLS regression

$$\beta_{MRPT}=\frac{\textsc{Cov}\left(\Delta_\tau\bar{p}_t,\Delta e_t\right)}{\textsc{Var}\left(\Delta e_t\right)}$$

recovers. First, we show that $\textsc{Cov}\left(\Delta_\tau\bar{p}_t,\Delta e_t\right)=\textsc{Cov}\left(\bar{p}_t,\Delta e_t\right)$. This follows from

$$\textsc{Cov}\left(\bar{p}_{t-\tau},\Delta e_t\right)=\mathbb{E}\left(\bar{p}_{t-\tau}\Delta e_t\right)-\mathbb{E}\left(\bar{p}_{t-\tau}\right)\mathbb{E}\left(\Delta e_t\right)=\mathbb{E}\left(\mathbb{E}_{t-\tau}\left(\bar{p}_{t-\tau}\Delta e_t\right)\right)-\mathbb{E}\left(\bar{p}_{t-\tau}\right)\mu=0$$

and $\mathbb{E}_{t-\tau}\left(e_t-e_{t-1}\right)=\mu$. To obtain this result, we have used the law of iterated expectations. Next, we use the definition of $\bar{p}_t$ from Lemma 1 to rewrite β as

$$\begin{aligned}
\beta_{MRPT}=\frac{\textsc{Cov}\left(\bar{p}_t,\Delta e_t\right)}{\textsc{Var}\left(\Delta e_t\right)}&=\frac{\textsc{Cov}\left(\left(1-\rho\theta\right)\sum_{s=0}^{\infty}(\rho\theta)^s\mathbb{E}_t\left(\tilde{p}_{t+s}\right),\Delta e_t\right)}{\textsc{Var}\left(\Delta e_t\right)}\\
&=\left(1-\rho\theta\right)\sum_{s=0}^{\infty}(\rho\theta)^s\frac{\textsc{Cov}\left(\mathbb{E}_t\left(\tilde{p}_{t+s}\right),\Delta e_t\right)}{\textsc{Var}\left(\Delta e_t\right)}\\
&=\left(1-\rho\theta\right)\sum_{s=0}^{\infty}(\rho\theta)^s\frac{\left(\mathbb{E}\left(\mathbb{E}_t\left(\tilde{p}_{t+s}\right)\Delta e_t\right)-\mathbb{E}\left(\mathbb{E}_t\left(\tilde{p}_{t+s}\right)\right)\mathbb{E}\left(\Delta e_t\right)\right)}{\textsc{Var}\left(\Delta e_t\right)}\\
&=\left(1-\rho\theta\right)\sum_{s=0}^{\infty}(\rho\theta)^s\frac{\left(\mathbb{E}\left(\mathbb{E}_t\left(\tilde{p}_{t+s}\Delta e_t\right)\right)-\mathbb{E}\left(\mathbb{E}_t\left(\tilde{p}_{t+s}\right)\right)\mathbb{E}\left(\mathbb{E}_t\left(\Delta e_t\right)\right)\right)}{\textsc{Var}\left(\Delta e_t\right)}\\
&=\left(1-\rho\theta\right)\sum_{s=0}^{\infty}(\rho\theta)^s\frac{\textsc{Cov}\left(\tilde{p}_{t+s},\Delta e_t\right)}{\textsc{Var}\left(\Delta e_t\right)},
\end{aligned}$$

where we have used again the law of iterated expectations. The last step of the proof consists of showing the last term in the previous equation is equal to MRPT.

From the definition of MRPT in equation (14)

$$\begin{aligned}
MRPT &= (1-\rho\theta)^2 \sum_{s=1}^{\infty} (\rho\theta)^{s-1} s \frac{\text{Cov}_t\left(e_{t+s}, \tilde{p}_{t+s}\right)}{\text{Var}_t\left(e_{t+s}\right)} \\
&= (1-\rho\theta)^2 \sum_{s=1}^{\infty} (\rho\theta)^{s-1} s \left(\frac{\text{Cov}_t\left(e_t + \Delta e_{t+1} + \ldots + \Delta e_{t+s}, \tilde{p}_{t+s}\right)}{\text{Var}_t\left(e_t + \Delta e_{t+1} + \ldots + \Delta e_{t+s}\right)}\right) \\
&= (1-\rho\theta)^2 \sum_{s=1}^{\infty} (\rho\theta)^{s-1} s \left(\frac{\text{Cov}_t\left(e_t + \Delta e_{t+1} + \ldots + \Delta e_{t+s}, \tilde{p}_{t+s}\right)}{s\text{Var}_t\left(\Delta e_{t+s}\right)}\right) \\
&= (1-\rho\theta)^2 \sum_{s=1}^{\infty} (\rho\theta)^{s-1} s \left(\sum_{j=1}^{s} \frac{\text{Cov}_t\left(\Delta e_{t+j}, \tilde{p}_{t+s}\right)}{s\text{Var}_t\left(\Delta e_{t+j}\right)}\right)
\end{aligned}$$

where the last equation uses $\text{Var}_t\left(\Delta e_{t+j}\right) = \text{Var}_t\left(\Delta e_{t+s}\right)$ for any $j, s \geq 1$. Let

$$\tilde{\Psi}_{j,s,t} \equiv \frac{\text{Cov}_t\left(\Delta e_{t+j}, \tilde{p}_{t+s}\right)}{\text{Var}_t\left(\Delta e_{t+j}\right)},$$

which is the pass-through of an exchange rate shock in period $t+j$ to prices in period $t+s$. Then, we can rewrite MRPT as

$$MRPT = (1-\rho\theta) \sum_{s=1}^{\infty} (\rho\theta)^{s-1} \left((1-\rho\theta) \sum_{j=1}^{s} \tilde{\Psi}_{j,s,t}\right). \tag{22}$$

An intermediate result (that we show below) is that

$$\tilde{\Psi}_{j,s,t} = \tilde{\Psi}_{s-j,t} = \frac{\text{Cov}_t\left(\Delta e_t, \tilde{p}_{t+s-j}\right)}{\text{Var}_t\left(\Delta e_t\right)}. \tag{23}$$

That is, pass-through is only a function of the time since the shock occurred, and not of the time it occurs. Imposing this result in the definition of MRPT (equation (22)), we obtain

$$MRPT = (1-\rho\theta) \left(\sum_{s=0}^{\infty} (\rho\theta)^{s} \frac{\text{Cov}_t\left(\Delta e_t, \tilde{p}_{t+s}\right)}{\text{Var}_t\left(\Delta e_t\right)}\right),$$

which is equal to the expression obtained for β_{MRPT}.

Finally, we show that equation (23) holds:

$$
\begin{aligned}
\textsc{Cov}_t\left(\Delta e_{t+j}, \tilde{p}_{t+s}\right) = \textsc{Cov}_t\Bigg(&\Delta e_{t+j}, \frac{\eta\alpha_T + (1-\eta)\alpha_N}{1-\sigma+\frac{\sigma}{\gamma}} e_{t+s} + \frac{\nu\omega}{1-\sigma+\frac{\sigma}{\gamma}}\Delta e_{t+s} + \frac{\left(1/\gamma-1\right)\alpha_w}{1-\sigma+\frac{\sigma}{\gamma}} e_{t+s} \\
&+ \frac{\left(\sigma-1\right)\left(1/\gamma-1\right)\alpha_{cpi}}{1-\sigma+\frac{\sigma}{\gamma}} e_{t+s}\Bigg) \\
&== \left(\frac{\eta\alpha_T + (1-\eta)\alpha_N}{1-\sigma+\frac{\sigma}{\gamma}} + \frac{\left(1/\gamma-1\right)\alpha_w}{1-\sigma+\frac{\sigma}{\gamma}} + \frac{\left(\sigma-1\right)\left(1/\gamma-1\right)\alpha_{cpi}}{1-\sigma+\frac{\sigma}{\gamma}}\right) var_t\left(\Delta e_{t+j}\right) \\
&== \left(\frac{\eta\alpha_T + (1-\eta)\alpha_N}{1-\sigma+\frac{\sigma}{\gamma}} + \frac{\left(1/\gamma-1\right)\alpha_w}{1-\sigma+\frac{\sigma}{\gamma}} + \frac{\left(\sigma-1\right)\left(1/\gamma-1\right)\alpha_{cpi}}{1-\sigma+\frac{\sigma}{\gamma}}\right) var_t\left(\Delta e_t\right).
\end{aligned}
$$

The equation (23) follows from the fact that the last equation does not depend on j nor s.

A.4 Proof of Proposition 1

The proof of the first part of the Proposition follows from the proof of Lemma 1. To prove the second set of results in this proposition we first compute the covariance term in (20):

$$
\textsc{Cov}_t\left(e_{t+s}, e_{t+s} - 2\tilde{p}_{t+s}\right) = s\textsc{Var}_t\left(\Delta e_t\right) - 2\textsc{Cov}_t\left(e_{t+s}, \tilde{p}_{t+s}\right), \tag{24}
$$

where in the first term we use the fact that the exchange rate follows a random walk. We can also compute the covariance between the exchange rate and the optimal flexible price (10):

$$
\begin{aligned}
\textsc{Cov}_t\left(e_{t+s}, \tilde{p}_{t+s}\right) = \textsc{Cov}_t\Bigg(&e_{t+s}, \frac{\eta\alpha_T + (1-\eta)\alpha_N}{1-\sigma+\frac{\sigma}{\gamma}} e_{t+s} + \frac{\nu\omega}{1-\sigma+\frac{\sigma}{\gamma}}\Delta e_{t+s} + \frac{\left(1/\gamma-1\right)\alpha_w}{1-\sigma+\frac{\sigma}{\gamma}} e_{t+s} && (25)\\
&+ \frac{\left(\sigma-1\right)\left(1/\gamma-1\right)\alpha_{cpi}}{1-\sigma+\frac{\sigma}{\gamma}} e_{t+s}\Bigg) \\
&= \textsc{Var}_t\left(\Delta e_{t+1}\right)\Bigg(\left(\frac{\eta\alpha_T + (1-\eta)\alpha_N}{1-\sigma+\frac{\sigma}{\gamma}} + \frac{\left(1/\gamma-1\right)\alpha_w}{1-\sigma+\frac{\sigma}{\gamma}} + \frac{\left(\sigma-1\right)\left(1/\gamma-1\right)\alpha_{cpi}}{1-\sigma+\frac{\sigma}{\gamma}}\right) s && (26)\\
&+ \frac{\nu\omega}{1-\sigma+\frac{\sigma}{\gamma}}\Bigg). && (27)
\end{aligned}
$$

Substituting (24) and (27) into (19), we obtain

$$
\begin{aligned}
\mathcal{L}_t \simeq &-\frac{\Pi_{ppt}\left(\tilde{p}_{t+s}\right)}{2} \\
&\sum_{s=0}^{\infty}\left(\rho\theta\right)^s\left(-\mu^2\left(\frac{\rho\theta}{1-\rho\theta} - s\right)^2\right. && (28)\\
&\left.+2\textsc{Var}_t\left(\Delta e_{t+1}\right)\left(\left(\frac{1}{2} - \frac{\eta\alpha_T + (1-\eta)\alpha_N + \left(1/\gamma-1\right)\left(\alpha_w + \left(\sigma-1\right)\alpha_{cpi}\right)}{1-\sigma+\frac{\sigma}{\gamma}}\right)s - \frac{\nu\omega}{1-\sigma+\frac{\sigma}{\gamma}}\right)\right). && (29)
\end{aligned}
$$

The comparative statics results follow directly by taking derivatives of $\mathcal{L}_t$ with respect to each parameter and evaluating their sign. The fifth result (i.e., $\frac{\partial \mathcal{L}}{\partial \eta} \leq 0$) also uses the assumption that $\alpha_T > \alpha_N$. For the second result, we use the fact that the importance of the second term, relative to the first term, diminishes as $\text{Var}_t(\Delta e_{t+1})$ becomes smaller. Therefore, for $\text{Var}_t(\Delta e_{t+1})$ low enough, the first term, which is always negative, dominates.

B Additional Tables and Figures

Table B.1: Comparison of Platform Categories and Harmonized System (HS) Categories

Mercado Libre Category	2018 HS Digit	Description
Electronics, Audio and Video — Televisions — LED	8	Reception apparatus for television, whether or not incorporating radio-broadcast receivers or sound or video recording or reproducing apparatus
Cellphones and Telephones — Cellphones and Smartphones — iPhone	6	Telephones for cellular networks or for other wireless networks
Sports and Fitness — Bicycles and Cycling — Bicycles	6	Bicycles and other cycles (including delivery tricycles), not motorized
Babies — Baby Caring Accessories — Strollers	8	Baby carriages (including strollers)
Home, Furniture and Garden — Bedroom — Mattresses and Bedsprings	8	Mattresses: Of cellular rubber or plastics, whether or not covered
Consoles and Video Games — PlayStation — Playstation 4 - PS4	8	Video game consoles and machines and parts and accessories thereof
Industries and Offices — Office Equipment — Stationery	4	Registers, account books, notebooks, order books, receipt books, letter pads, memorandum pads, diaries and similar articles, exercise books, blotting pads, binders (looseleaf or other), folders, file covers, manifold business forms, interleaved carbon sets and other articles of stationery, of paper or paperboard; albums for samples or for collections and book covers (including cover boards and book jackets) of paper or paperboard
Musical Instruments — Guitars — Electric	8	Musical instruments, the sound of which is produced, or must be amplified, electrically (for example, organs, guitars, accordions): Other
Cameras and Accessories — Digital Memory Cards — SD	8	Semiconductor media: Solid-state non-volatile storage devices
Clothes, Shoes and Accessories — T-shirts — Women	8	T-shirts: Of cotton: Women's

Notes: This table compares the classification system used by the online platform with the HS classification used in international trade. The first column includes common categories of goods classified at level 3 on the platform. Columns 2 and 3 show the digit and description of the closest category found in the 2018 US Harmonized System.

Table B.2: Number of Listings and Sellers by Country

Country	Number of Listings	Number of Sellers	Random Sample
Argentina	18,594,13	1,751,160	100%
Bolivia	13,695	2,847	100%
Costa Rica	232,530	40,493	100%
Dominican Republic	1,220,326	22,091	30%
Guatemala	33,704	3,278	100%
Honduras	2,383	769	100%
Mexico	17,711,34	1,086,456	5%
Nicaragua	2,534	796	100%
Panama	41,526	5,033	100%
Paraguay	16,674	2,798	100%
Peru	2,277,882	319,246	30%
Uruguay	3,604,848	269,319	30%
Total	43,751,575	3,504,286	-

Notes: This table shows the platform's size in terms of the number of unique listings and sellers by country, before restricting and cleaning the data. Given the daily frequency of the data, we select a random sample of listings due to computational considerations. The last column presents the size of the random sample by country. We exclude data from the goods market in Argentina, where dollar pricing has not been allowed since 2012. Given the reduction of the sample size, there is no computational need to reduce the sample size in Argentina.

Table B.3: Summary Statistics: Sellers

	Mean	SD	P10	P25	P50	p75	p90	p99
Panel A: Historical Data								
Age in years	4.8	4.3	0.4	1.1	3.5	7.6	11.6	16.1
Number of transactions	66.5	1364.9	0.0	0.0	0.0	5.0	31.0	949.0
Number of transactions (> 0)	137.5	1959.4	1.0	2.0	5.0	22.0	104.0	2127.0
Panel B: Current Data								
Number of listings	6.9	693.4	1.0	1.0	1.0	2.0	4.0	67.0
Number of transactions	7.5	546.3	0.0	0.0	0.0	0.0	1.0	52.0
Number of transactions (> 0)	34.6	1172.7	1.0	1.0	1.0	2.0	10.0	427.0
Total revenues	167460.0	1.1e+07	0.0	0.0	0.0	0.0	5295.1	194196.8
Total revenues (> 0)	772054.9	2.4e+07	155.7	1070.1	4627.8	10723.9	30935.6	5.6e+06

Notes: This table presents summary statistics at the seller level for all countries. Panel A shows moments of the distribution of sellers' experience (age) and the number of transactions (unconditional, and conditional on having made at least one transaction) ever made in the platform. Only transactions in the goods market are included. Panel B shows moments of the distribution of sellers' listings, transactions and revenues, computed from the micro data collected during March-October 2018 in all markets (goods, vehicles, and real estate).

Table B.4: Summary Statistics: Listings

Category	% Foreign Curr.	# Listings	# Sellers	Avg. Price	SD. Price	Top Items
Elect., audio, video	17%	160,994	14,928	163.67	253.03	Portable speakers, LED TVs, Headphones
Cameras and accessories	4%	163,246	5,082	329.69	586.40	Lenses, Digital videocameras, SD cards
Cellphones and phones	12%	210,811	25,681	123.12	200.62	Samsung smartphone, iPhone, LG smartphone
Games and toys	3%	88,915	9,103	51.68	65.96	Teddy bears, Cars with remote controls, Blocks
Videogames	12%	55,155	8,712	83.27	115.41	Nintendo Wii, Playstation 4, Xbox One
Music instruments	11%	28,651	3,009	265.22	348.12	Electric guitars, Keyboards, Drums
Health and beauty	0%	411,119	16,867	59.79	47.54	Lipsticks, Moisturizers, Perfumes for women
Sports and fitness	14%	107,412	14,970	77.97	106.11	Camping lamps, Soccer shirts, Bicycles
Baby related	7%	31,361	5,943	51.01	68.12	Strollers, Diapers, Cribs
Clothing	5%	277,050	38,996	44.27	40.52	Wallets, Sneakers for men, Pants for women
Real Estate	49%	2,277,113	172,198	161,397.93	241,436.34	Apartments for rent, Houses for sale, Offices for rent
Industries, office	18%	125,212	14,389	170.77	366.66	Ladders, Paint, Electrical tools
Home, furniture, appliances	9%	272,532	27,193	128.51	208.62	Mattresses, Space heaters, Cooking stoves
Computers	11%	515,596	16,611	154.78	278.55	Keyboards, Video cards, Hard drives
Vehicles	11%	2,184,255	788,559	10,273.91	9,278.73	BMW, Ford, Volkswagen
Car accessories	11%	149,700	13,538	105.09	154.60	Tires for cars, Parts: brakes, Parts: transmission
Jewelry	2%	126,235	9,473	194.52	281.79	Necklaces, Pendants, Watches for women

Notes: This table presents summary statistics for all listings on the platform, by broad categories of goods. The first column shows the fraction of prices set in dollars. The second and third columns show the number of listings and sellers in each category. The fourth and fifth column show the average price and the standard deviation of prices within the category. The last column shows the most common types of goods (categorized at level 3) within broad categories.

Table B.5: Price Dollarization and Sellers' Characteristics

	Dollarization of Revenues			Multi-Currency Sellers		
Country	Small	Medium	Large	Small	Medium	Large
Goods						
Argentina	.%	.%	.%	.%	.%	.%
Mexico	0%	0%	0%	1%	0%	1%
Uruguay	3%	11%	22%	9%	17%	32%
Peru	2%	2%	7%	3%	4%	12%
Average	2%	4%	10%	4%	7%	15%
Vehicles						
Argentina	0%	1%	7%	3%	4%	18%
Mexico	0%	0%	1%	1%	0%	2%
Uruguay	21%	91%	99%	30%	24%	15%
Peru	19%	81%	94%	19%	16%	16%
Average	10%	43%	50%	13%	11%	13%
Real Estate						
Argentina	2%	26%	96%	18%	32%	85%
Mexico	0%	1%	8%	0%	3%	40%
Uruguay	6%	34%	100%	30%	36%	66%
Peru	3%	9%	65%	10%	13%	23%
Average	3%	17%	67%	15%	21%	54%

Notes: This table analyzes currency choice by sellers. The sample is restricted to sellers with positive revenues from active listings during March-October 2018. Columns 1-3 show the share of revenues that correspond to listings posted in dollars for each country and type of good, by tercile of sellers' revenues in dollars. Columns 4-6 show the share of sellers that post goods in multiple currencies. This sample is further restricted to sellers with more than one listing. For the goods market in Argentina, dollar pricing has not been allowed since 2012 (dollar pricing is still allowed for vehicles and real estate).

Table B.6: Price Dollarization and Sellers' (Weighted) Characteristics

	Dollarization of Revenues			Multi-Currency Sellers		
Country	Small	Medium	Large	Small	Medium	Large
Goods						
Argentina	.%	.%	.%	.%	.%	.%
Mexico	0%	0%	0%	1%	1%	5%
Uruguay	12%	31%	40%	19%	67%	69%
Peru	3%	23%	12%	6%	32%	31%
Average	5%	18%	17%	9%	33%	35%
Vehicles						
Argentina	2%	19%	20%	9%	62%	63%
Mexico	0%	3%	4%	1%	7%	11%
Uruguay	69%	99%	100%	23%	16%	23%
Peru	53%	94%	96%	17%	18%	13%
Average	31%	54%	55%	12%	26%	28%
Real Estate						
Argentina	40%	97%	98%	51%	98%	96%
Mexico	3%	19%	19%	18%	90%	93%
Uruguay	46%	100%	100%	47%	70%	100%
Peru	21%	96%	100%	15%	26%	21%
Average	27%	78%	79%	33%	71%	78%

Notes: This table analyzes currency choice by sellers. The sample is restricted to sellers with positive revenues from active listings during March-October 2018. Columns 1-3 show the share of revenues that correspond to listings posted in dollars for each country and type of good, by tercile of sellers' revenues in dollars. To construct the terciles we weighted each observation by the total revenues of sellers. Columns 4-6 show the share of sellers that post goods in multiple currencies. This sample is further restricted to sellers with more than one listing. For the goods market in Argentina, dollar pricing has not been allowed since 2012.

Table B.7: Pass-Through Conditional on Price Change: Country-Market Evidence

	Share w. Model-Consistent Predictions	# Categories
	Panel A: by Country	
Argentina	80%	35
Uruguay	71%	157
	Panel B: by Market	
Goods	69%	141
Vehicles	83%	24
Real Estate	81%	27

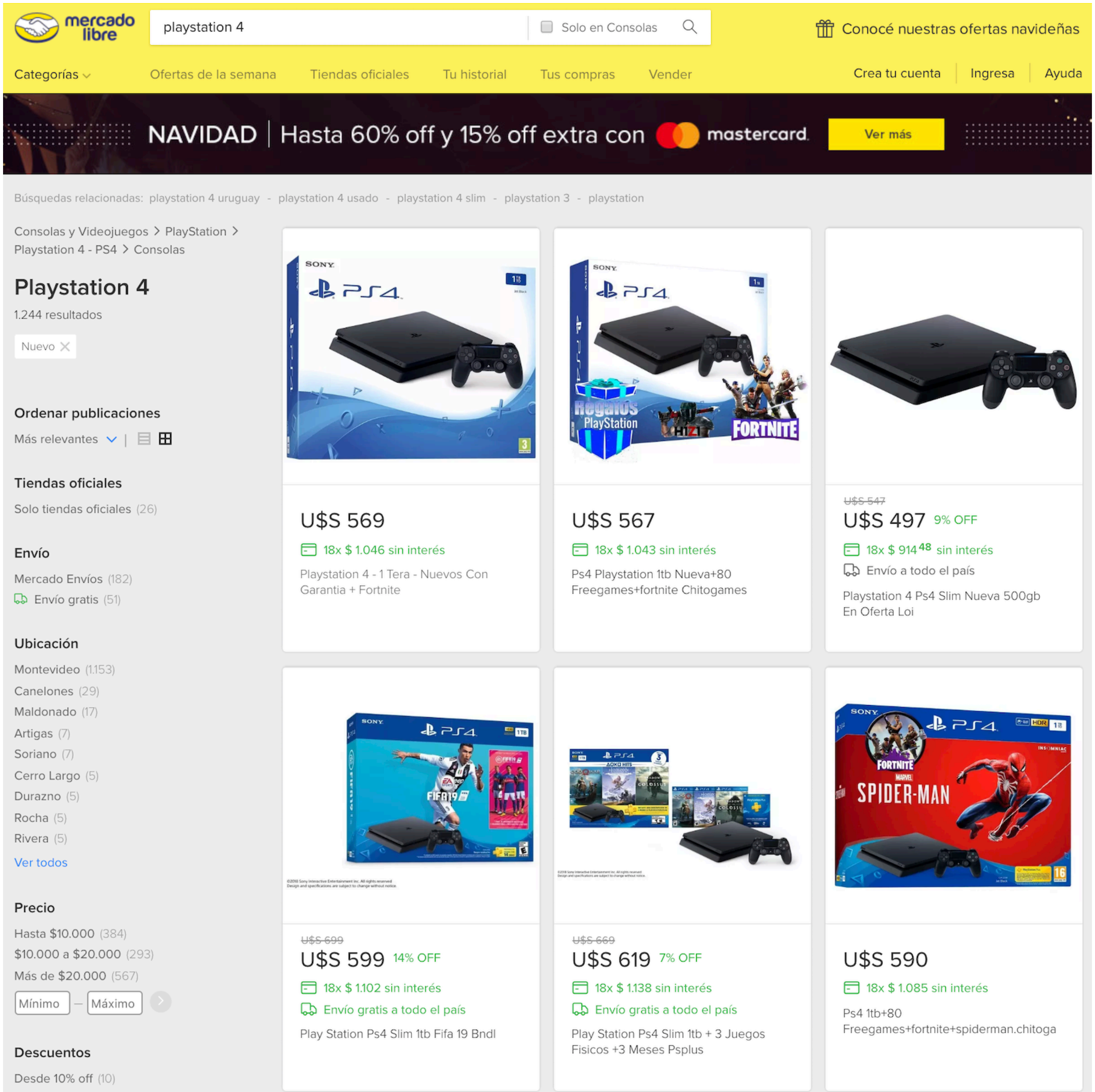
Notes: This table reports the share of category-currency pairs with estimated MRPT in accordance with the theory—i.e. MRPT above the cutoff derived in Proposition 1 for dollar-priced goods and MRPT below the cutoff for goods priced in local currency. The last column reports the number of markets included in each share. Since not all markets contain enough observations of goods priced in both currencies, we estimate equation (6) with OLS for each category-currency separately, where we use the second level of disaggregation offered by the platform to define a market, and only consider estimates of MRPT for category-currency pairs that have at least 100 observations. To construct the MRPT cutoff we use country-specific observed inflation and volatility of nominal exchange rate, country-category-specific price stickiness in local currency, and a annualized discount factor of 0.96. In the market for real estate, we adjust the discount factor to take into account the fact that the seller's objective is to sell a single unit of real estate, which occurs in 5 months on average.

Table B.8: Price Dollarization and Pass-Through: Country-Market Evidence

	1 month	6 months	12 months	18 months	24 months
Goods	44.8%	22.6%	30.7%	38.6%	12.1%
Vehicles	67.5%	58.9%	41.6%	36.1%	64.8%
Real Estate	33.7%	57.7%	60.8%	50.8%	47.1%
All	49.0%	66.9%	42.2%	38.0%	31.7%

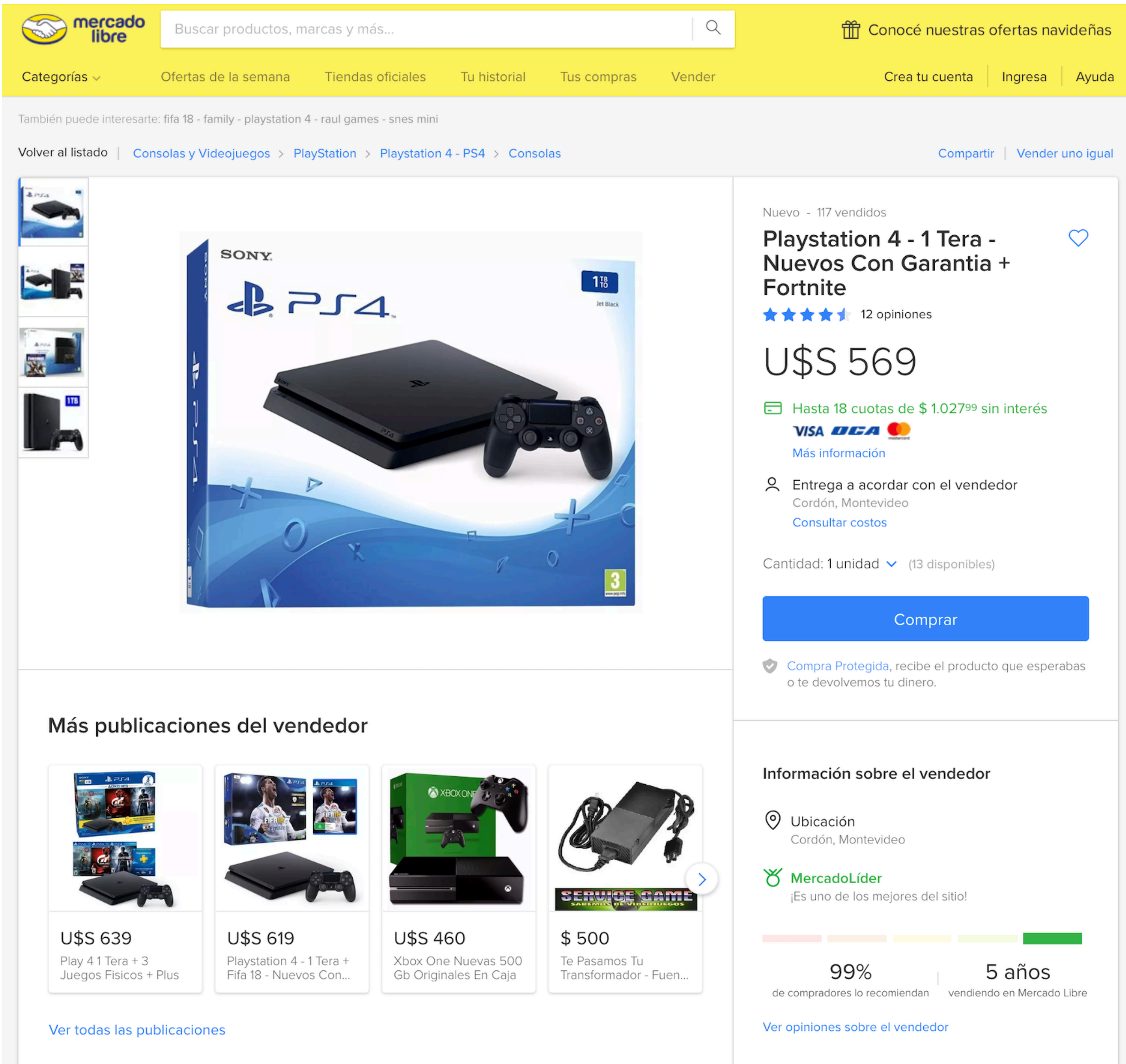
Notes: This table reports the cross-country correlations between the share of prices in dollars (computed with data from the online platform) and the estimated cumulative pass-through at different horizons for each country-market. We construct good-specific CPIs out of those level 2 categories of the CPI that contain goods that are offered in the online platform. Vehicle-specific CPIs correspond to the "vehicles" categories of the CPI. Real estate-specific CPIs correspond to the "rent" categories of the CPI. We provide more details of the construction of the indices in Appendix C.6.

Figure B.1: Screenshot of Online Platform at the Search Stage



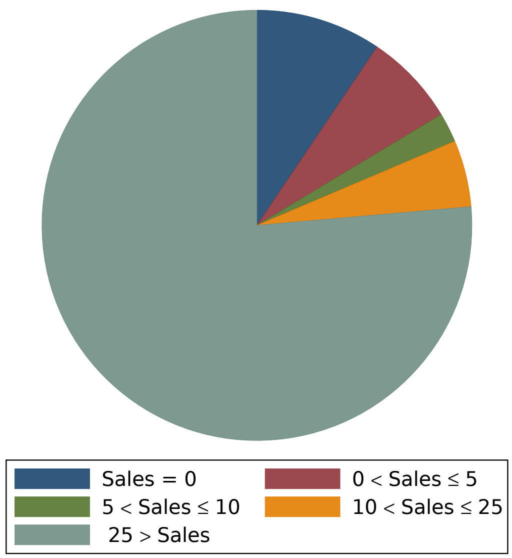
Notes: This figure shows an example of what the platform displays when a potential buyer searchers for a "Playstation 4" in Mercado Libre-Uruguay.

Figure B.2: Screenshot of Online Platform at the Listing Level



Notes: This figure shows how a listing is displayed to a potential buyer of a "Playstation 4" in Mercado Libre-Uruguay.

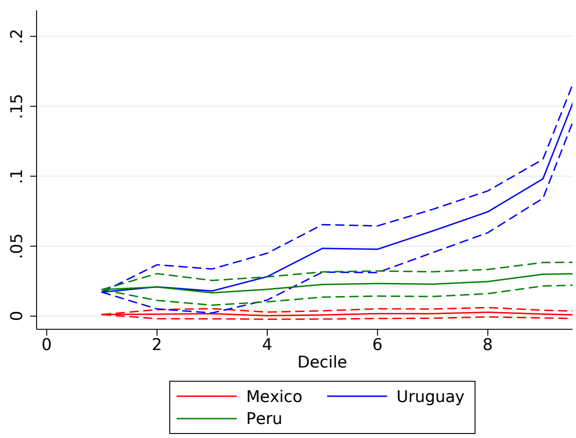
Figure B.3: Distribution of Listings by Sellers' Sales



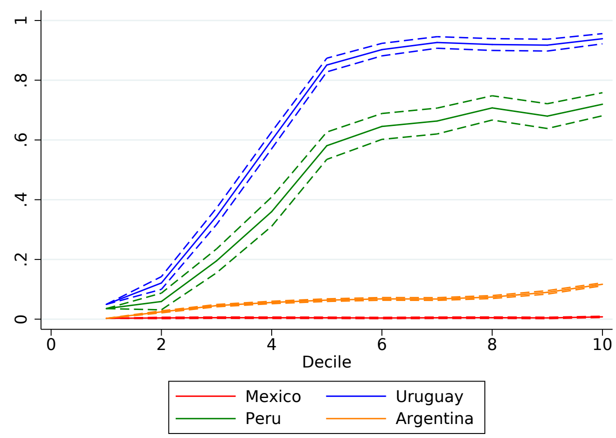
Notes: This figure shows the concentration of listings in the goods market and across all countries, by sellers with different number of sales made in active listings during March-October 2018.

Figure B.4: Price Dollarization by Sellers' Size

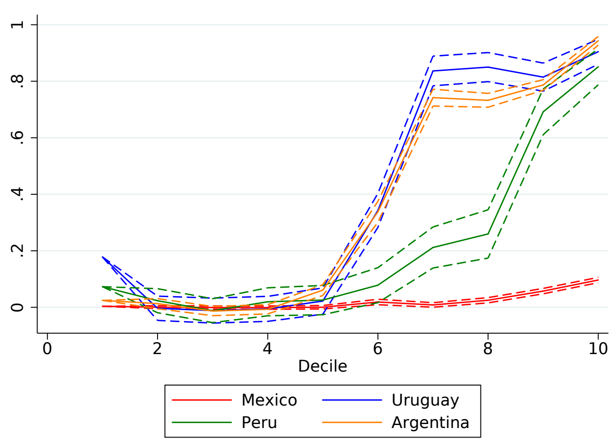
(a) Goods



(b) Vehicles

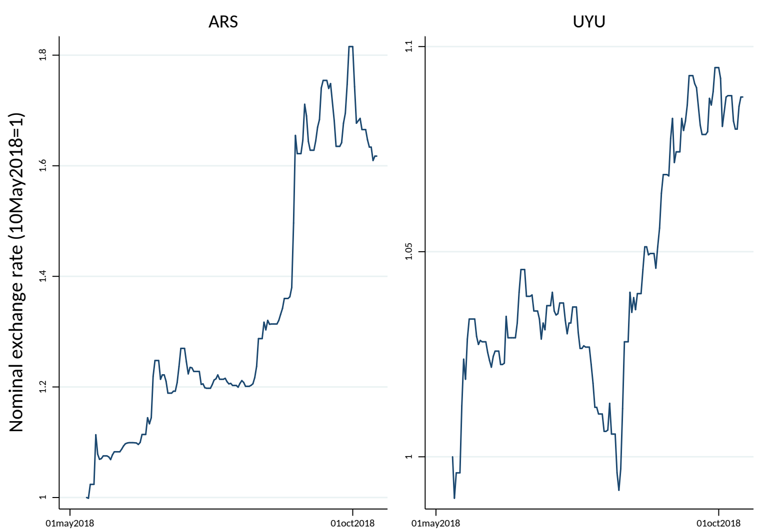


(c) Real Estate



Notes: The panels plot the point estimates of an OLS regression of a seller's share of revenues that correspond to listings posted in dollars on a categorical variable indicating the sellers' decile of total revenues in dollars and category fixed effects. The dashed lines indicate 95% confidence intervals constructed with robust standard errors. We estimate one regression for each country and type of good. The sample is restricted to sellers with positive revenues from active listings during March-October 2018. For the goods market in Argentina, dollar pricing has not been allowed since 2012.

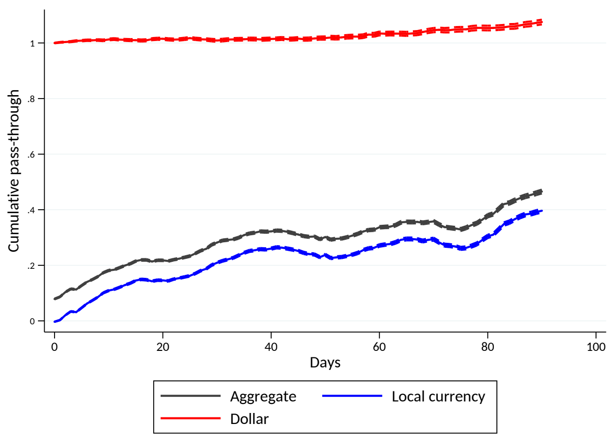
Figure B.5: Nominal Exchange Rate: Argentina and Uruguay



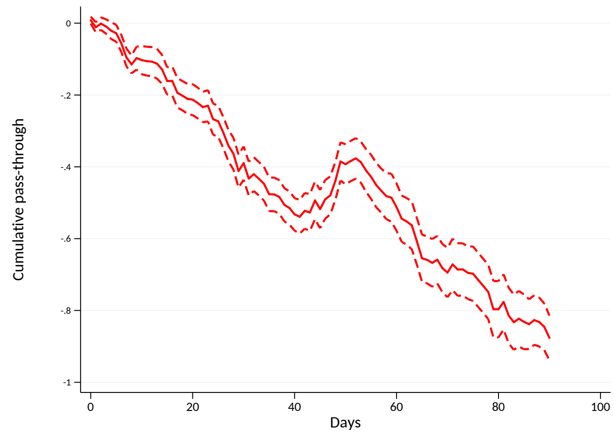
Notes: This figure shows the bilateral nominal exchange rate between the Argentinean Peso and the US dollar (left), and the Uruguayan Peso and the US dollar (right), during the period of analysis (March-October 2018). The nominal exchange rate has been normalized to 1 on the first day of the sample.

Figure B.6: Exchange Rate Pass-through to Prices and Quantities: Argentina

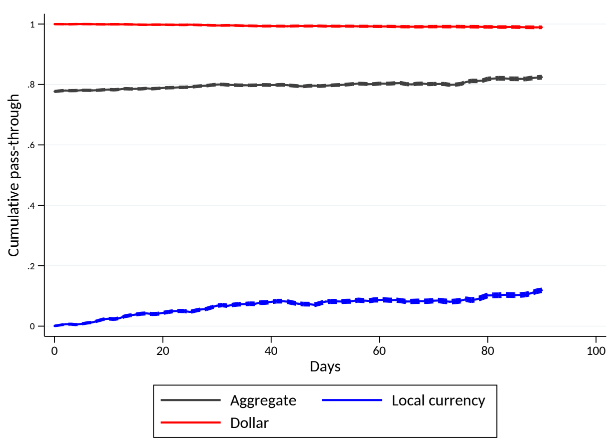
(a) Vehicles: Prices



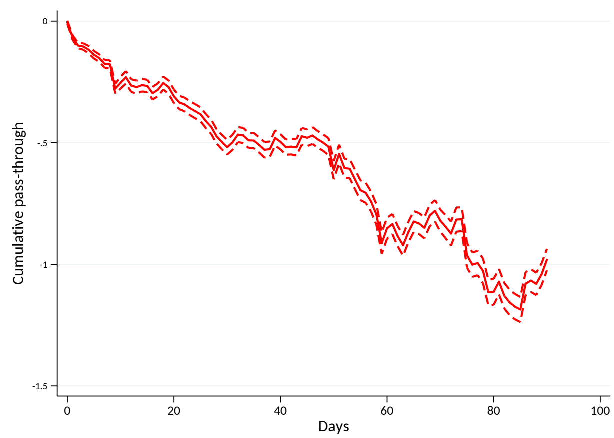
(b) Vehicles: Quantities



(c) Real Estate: Prices



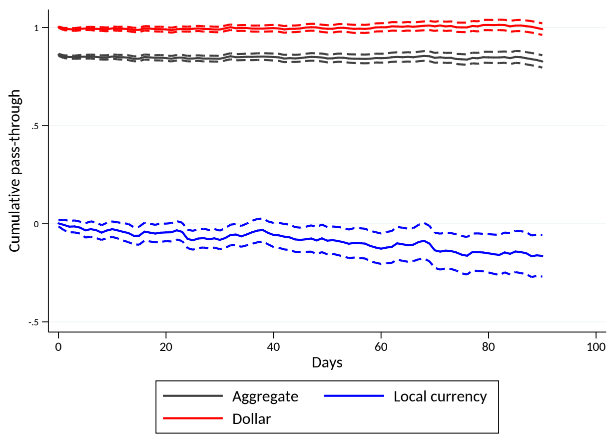
(d) Real Estate: Quantities



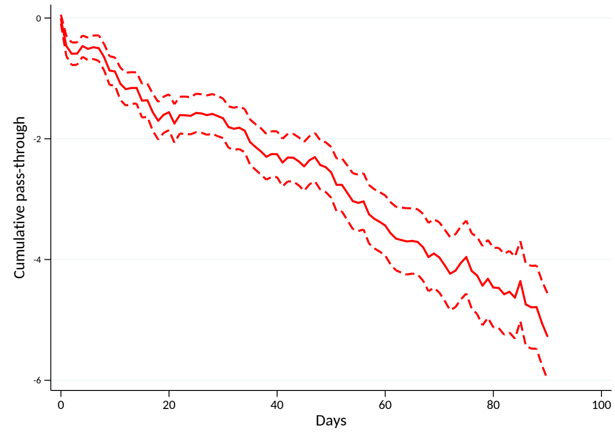
Notes: These figures show the estimated pass-through to prices (in Panels B.6a and B.6c) and quantities (in Panels B.6b and B.6d) for Argentina in markets for vehicles and real estate. Panels B.6b and B.6d presents estimates of pass-through to quantities sold of listings posted in dollars relative to quantities sold of listings posted in local currency. Dashed lines correspond to 95% confidence intervals (standard errors are clustered at the listing level).

Figure B.7: Exchange Rate Pass-through to Prices and Quantities: Uruguay

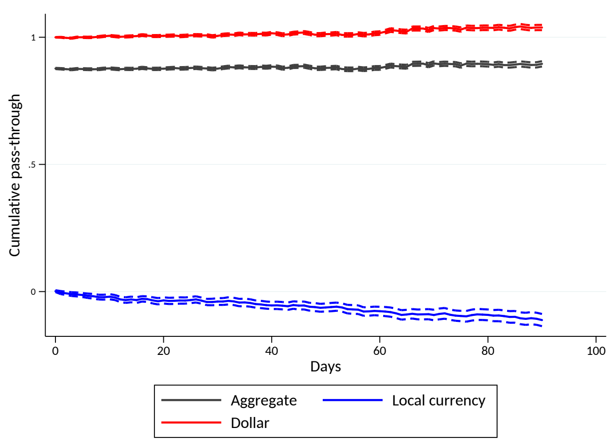
(a) Vehicles: Prices



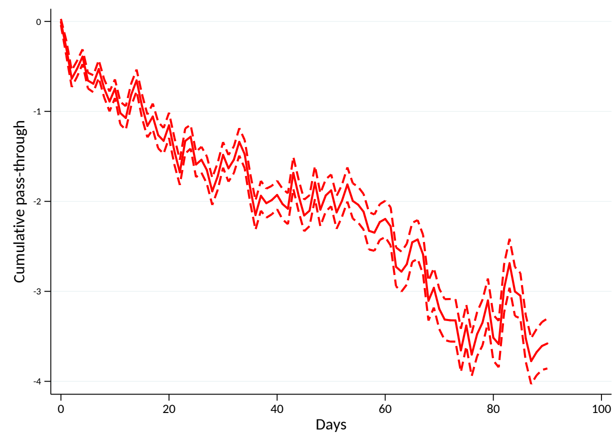
(b) Vehicles: Quantities



(c) Real Estate: Prices



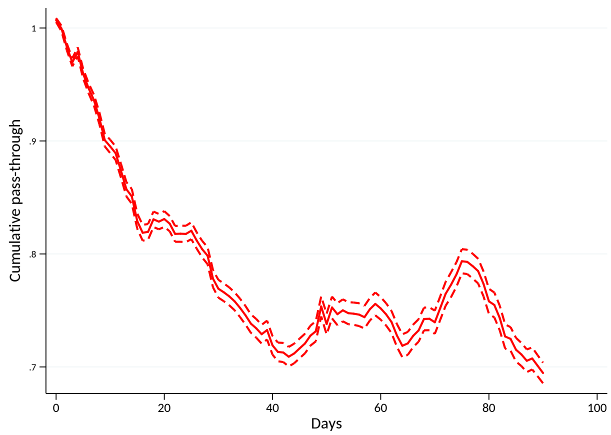
(d) Real Estate: Quantities



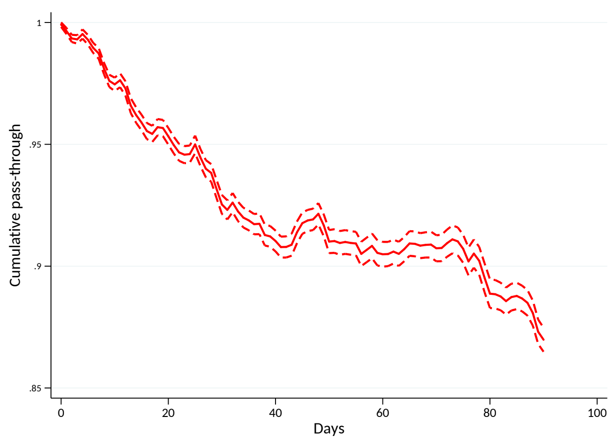
Notes: These figures show the estimated pass-through to prices (in Panels B.7a and B.7c) and quantities (in Panels B.7b and B.7d) for Uruguay in markets for vehicles and real estate. Panels B.7b and B.7d presents estimates of pass-through to quantities sold of listings posted in dollars relative to quantities sold of listings posted in local currency. Dashed lines correspond to 95% confidence intervals (standard errors are clustered at the listing level).

Figure B.8: Exchange Rate Pass-through with Time FE: Argentina

(a) Vehicles: Prices



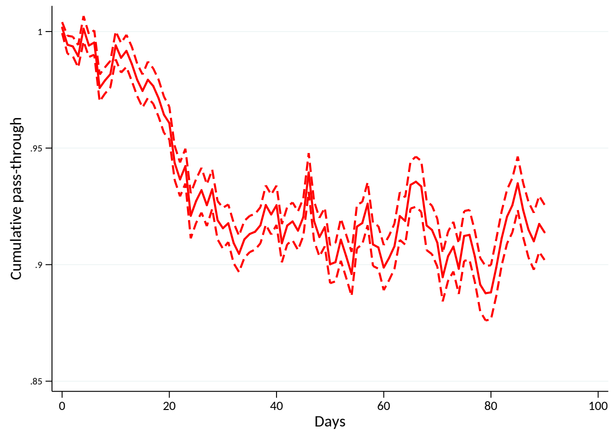
(b) Real Estate: Prices



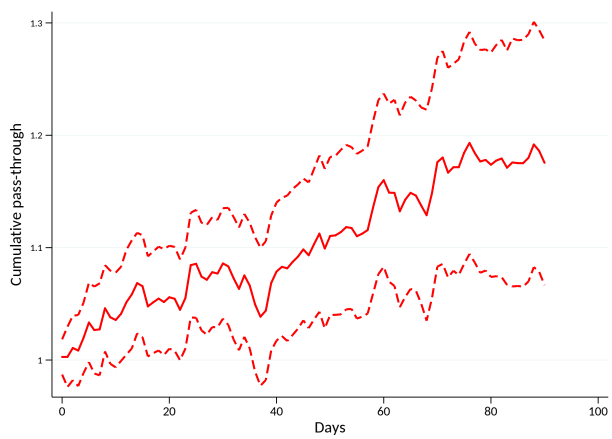
Notes: These figures show the estimated pass-through to prices for Argentina in markets of vehicles and real estate. Panels present estimates of pass-through to prices of listings posted in dollars relative to prices of listings posted in local currency (equation (7)). Dashed lines correspond to 95% confidence intervals (standard errors are clustered at the listing level).

Figure B.9: Exchange Rate Pass-through with Time FE: Uruguay

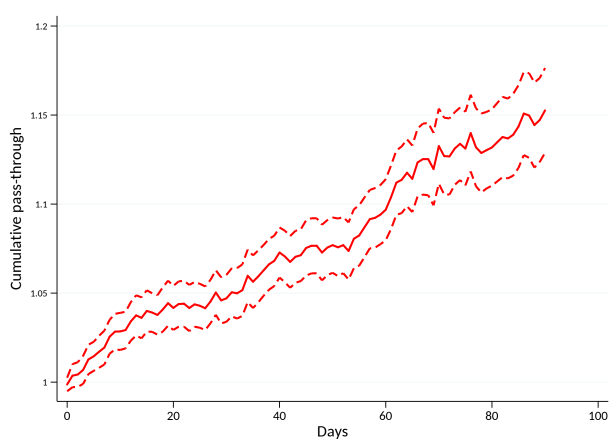
(a) Goods: Prices



(b) Vehicles: Prices

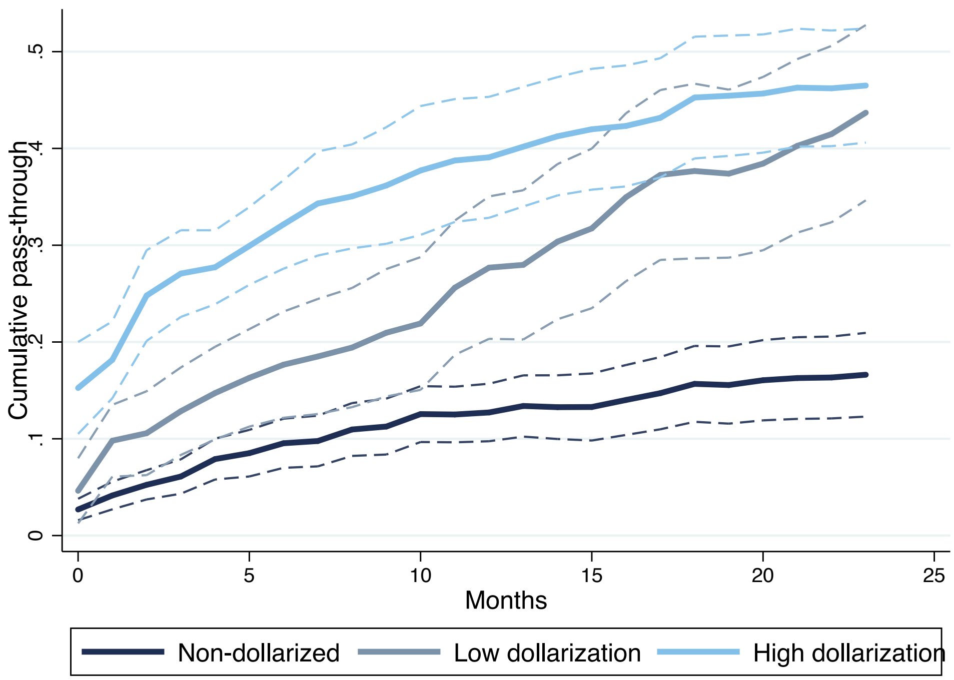


(c) Real Estate: Prices



Notes: These figures show the estimated pass-through to prices for Uruguay in markets of goods, vehicles and real estate. Panels present estimates of pass-through to prices of listings posted in dollars relative to prices of listings posted in local currency (equation (7)). Dashed lines correspond to 95% confidence intervals (standard errors are clustered at the listing level).

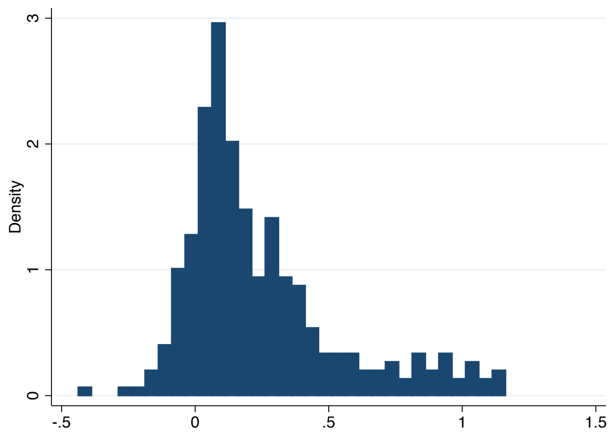
Figure B.10: Price Dollarization and Aggregate Exchange Rate Pass-Through



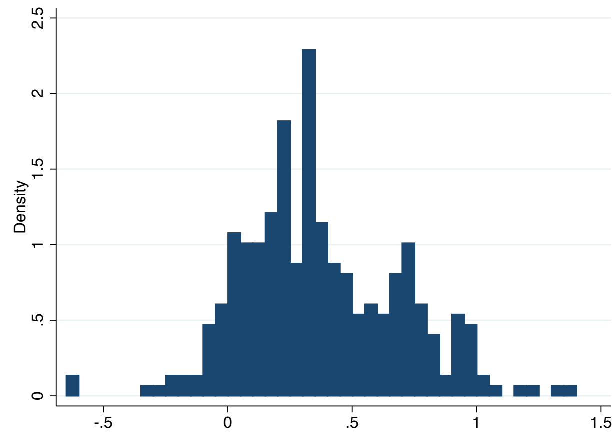
Notes: This figure shows the estimated pass-through to aggregate CPIs in three groups of countries: zero dollarization (Brazil, Chile, and Colombia), low dollarization (Mexico and Costa Rica), and high dollarization (Argentina, the Dominican Republic, Guatemala, Paraguay, Peru, and Uruguay). Dashed lines correspond to 95% confidence intervals.

Figure B.11: Exchange Rate Pass-through to Prices in Uruguay: All Products

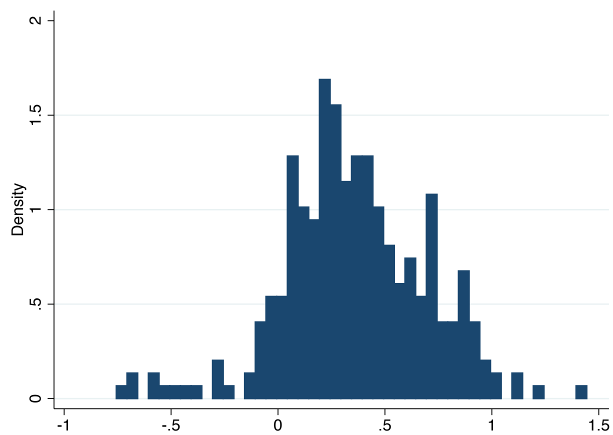
(a) 1M Pass-through



(b) 6M Pass-through



(c) 12M Pass-through



Notes: These figures present histograms of estimates of exchange rate pass-through for all goods included in the CPI in Uruguay. Panels (A), (B) and (C) present estimates at the 1-, 6- and 12-month horizon, respectively.

C Data Description

C.1 Description of the Online Platform

The following facts illustrate the importance of the platform in the regional e-commerce market. In 2017, the platform sold 271 million items with a combined gross merchandise value of USD11.8 billion (26% of all e-commerce sales in Latin America).[15] In the same year, 10 million unique sellers and 33.7 million unique buyers used the platform. With 56 million unique visitors in May 2018, Mercado Libre is the top retail site in Latin America, followed by Amazon (22.4mm), B2W (16.1mm), Alibaba (11.8mm), and eBay (9.5mm).[16]

In addition to providing intermediation services to buyers and sellers, the platform offers two services to overcome the largest barriers to e-commerce in Latin America: shipping infrastructure and access to electronic means of payment. Buyers can purchase goods on the platform by using the firm's own digital payment system, "MercadoPago", which is similar to PayPal and links payments to individual accounts in the system, external bank accounts, or credit/debit cards (around 80% of transactions occur through MercadoPago). Buyers can choose the currency with which to pay, regardless of the currency of the posted price. However, if a buyer decides to buy in local currency a good that is posted in dollars, Mercado Libre automatically converts the value of the good using the spot exchange rate plus a spread (acting thereby as a foreign exchange transaction business). As a result, buyers must pay an implicit transaction fee to the platform if they choose to pay with a different currency. In addition, Mercado Libre launched "MercadoEnvio", a logistics service that arose from alliances with the biggest logistics companies in each country (around 70% of transactions used this shipping method).[17]

One might question the usefulness of online data/e-commerce as a source of data on prices and quantities. Online sales as a share of total retail are 2% in Latin America, which is not much smaller than the share in advanced economies (around 8% in Europe and the US).[18] However, this is a fast growing market, with online sales growing by more than 20%

[15]See *Retail e-commerce sales in Latin America* from Statista.

[16]See *Most popular online retailers in Latin America* from Statista.

[17]In order to sell and buy in this platform, users need to create a country-specific account. Despite this possibility, users of the platform in one country cannot make purchases in the platform's site of another country. We verified the shipping options in our dataset and there is no listing that offers international shipping.

[18]See *e-commerce share of total global retail sales in 2016, by region*, from Statista.

annually in the last two years in all the major countries. In addition, Cavallo (2017) shows that a large fraction of online prices is identical to the corresponding "offline" price in the physical store.

On the platform, sellers have incentives to keep the information in their listing updated, since it is costly to use the platform's services; the cost of listing a good for sale for an unlimited duration is 11% of the transacted price. Ads in the markets for real estate and vehicles have a fixed duration (30, 60, 90, or 180 days). The lowest cost of listing a real estate ad for 60 days goes from USD9 (for individuals) to USD142 (for professional realtors who list multiple properties). The lowest cost of listing an ad for a vehicle for 60 days goes from USD9 (for individuals) to USD124 (for professional car dealers who list multiple units). Histograms of duration of listings and sellers are shown in Figures **??** and **??**. The three modes that can be observed correspond to listings that expired after 30 and 60 days, and those with unlimited duration that remained active during the entire window of observation. In the case of the goods market, sellers must also pay attention to inventories, since the listing will be paused (not visible to buyers) whenever the quantities available for sale reach zero and until sellers update the inventory to a positive number. Given these costs and the presence of big firms (including large well-known local firms, international brands, professional realtors, and car dealers), data from this online platform should be reliable.

C.2 Data Collection

The data collection process is facilitated by the provision of APIs by the platform in order to help developers create online apps to help sellers improve their sales. Every morning, a Java script begins collecting data from all listings available on the platform, by combining information on listings already stored in our dataset with new listings created during the previous day. Our code first creates a list of all listings across three groups of markets and all countries. Then, in a second round, it collects data on each specific listing. The idea behind this second step is to recover almost all of the information a user observes when deciding whether to purchase an item from a listing (see Figure B.2). There are only two exceptions to this rule. First, we do not save the pictures sellers include in the listing. Second, we record the title describing the good and the category tree used by the platform to categorize the good, but not any additional text the seller includes to further describe the good (due to computational constraints). In an additional step, the code downloads the full category three across all countries and summary information at the seller level.

C.3 Data cleaning and variable construction

Before using the micro data in the analysis, we implement a series of procedures to clean the data. The following filters are applied to listings for goods. First, we drop all observations coming from listings of "divisible" goods. In order to implement this filter, we make use of the description of the good that sellers include in the listing and the description of the category provided by the platform to isolate two types of listings: (1) those with sales in bulk, and (2) those with "divisible" goods. More specifically, we delete all listings that contained any of the following texts (in Spanish): promotion, batch, kilo (and variations), gram (and variations), liter (and variations), meter (and variations), centimeter (and variations), kilometer (and variations), pack, units, and "2 for 1". Based on this, we are able to identify the categories of goods in which these words appeared more often and dropped them completely. In addition, we delete categories containing heterogeneous goods. Overall, we delete all listings in the following categories: Music, Books and Movies, Art and Antiquities, Food and Beverages, Services, Collectibles and Hobbies, Pet related, and Other.

Next, we delete all listings for used goods (except listings for used cars and properties). We delete goods with high prices—i.e., those with prices above US$10,000 and above the 99th percentile of the within-category price distribution (after converting all prices into the same currency). Regarding listings for real estate and vehicles, we apply an algorithm to delete listings with "unusual" prices (e.g., 1, 9999999, etc.). We also drop listings that experienced log price changes above 100% in absolute terms. Finally, we delete all daily observations in which the listing was temporarily paused (buyers do not see paused listings), either by the seller or because the listing ran out of units available for sale. We also delete data on market-country pairs (there are three markets: goods, real estate, and vehicles) without any dollar pricing. After applying these filters, we end up with 434 million listing-day observations across all markets and countries.

An important variable in our analysis is the number of units sold by listing. As shown in Figure B.2, the platform keeps track of the cumulative number of quantities sold (e.g., "117 sold"). Therefore, the number of units sold in any given day can be obtained by subtracting the current value of this number from the one downloaded the previous day. This procedure introduces a small amount of measurement error when inferring the price at which each quantity was sold, since we only have data on one price per day. However, the importance of this measurement error should be trivial due to the persistence of prices and the high frequency of the data. When analyzing real estate and vehicles markets, we will consider the day of the sale as the day in which the seller decided to close the ad, as long as that date is earlier than the expiration date of the listing (in this market, sellers pay to list the ad for a fixed number of days, usually 30, 60, 90, or 180 days after which they can relist the same ad by paying again). An important feature of the platform is that closed listings cannot be reactivated. Thus, there are two reasons to close an ad before its expiration date: the property/vehicle was sold, the sellers does not want to sell it anymore.

Finally, we observe all price changes that occur during the life of a listing. We may not observe a price change that occurs if the seller decides to relist a good in a new listing with a different price once the original listing is closed. This is not a major concern since the average life of a listing is 35, 82, and 57 days in the market for vehicles, goods, and real estate, respectively.

C.4 Sample of Countries

The choice of the sample of country varies across exercises and is based on the objective of each exercise. For the cross-country analysis pursued in Sections 4.1 and 6, we include the 12 countries that display some degree of price dollarization, namely Argentina, Bolivia, Costa Rica, the Dominican Republic, Guatemala, Honduras, Mexico, Nicaragua, Panama, Paraguay, Peru, and Uruguay.[19] We also include 3 more countries (Brazil, Chile and Colombia), which have zero price dollarization due to regulation, as they are useful to understand the cross-country differences. Results are robust to excluding these countries from the analysis.

For the within-country analysis in Section 4.2, given that the focus is the selection at the micro-level into different currencies, we narrow down the attention to the countries with the largest amount of data and some degree of price dollarization. These countries are Argentina, Mexico, Peru, and Uruguay. For the analysis of the role of tradeability we use the historical dataset that covers data for Uruguay and Argentina for the 2003-12 period. This is the most suitable data in terms of period of analysis, given that the information on

[19]Even though Panama has a fixed exchange rate vis-a-vis the dollar, it still displays variation in the currency of denomination of prices, which motivate us to include Panama in our analysis. All main results are robust to excluding Panama from the analysis.

goods tradeability, is obtained from trade and sectoral output data for the years of 2002 for Argentina, and 2007 for Uruguay. Finally, for the pass-through analysis we focus on the case of Argentina and Uruguay, since these are economies with large amount of data, some degree of price dollarization and sufficient variation in the exchange rate during the period of analysis.

C.5 Tradeability Indices

We construct tradeability indices for 3-digit ISIC manufacturing industries as the ratio between the sum of exports and imports over output. We obtain trade data for Argentina and Uruguay from UN Comtrade World Integrated Solutions (WITS) and data on sectoral output from UNIDO. Due to data availability issues, we use data from 2002 for Argentina and data from 2007 for Uruguay. These data are merged using product concordance tables provided by WITS.

Next, we *manually* assign a 3-digit ISIC classification to each category of goods available on the online platform, by reading the description of each category and finding the closest match in the ISIC classification manual (United Nations (2008)). For those few categories with more than one possible 3-digit ISIC classification, we computed the tradeability index by first aggregating imports, exports, and output of all of these sectors and then computing the ratio. Aggregate statistics are reported in Table C1. As expected, due to its size, Uruguay is relatively more open to trade than Argentina. Additionally, more technologically advanced products (e.g., cameras and computers) tend to be more imported in both economies, whereas local production of clothing tends to be more relevant than imports of those goods. Table C1 also reports an additional measure of tradeability defined as the ratio of the sum of exports and imports to output, which yields results similar to the baseline measure.

C.6 Other sources of data

When analyzing the relevance of currency choice for broader aggregates, we use monthly data for the 1990-2018 period (subject to data availability in each country). Data on deposit dollarization, monthly nominal exchange rates and inflation rates of Latin American countries were obtained from the Latin Macro Watch dataset produced by the IADB. Data on trade openness were obtained from the World Bank. Data on the US monthly inflation rate were obtained from the FRED database produced by the Federal Reserve Bank of St. Louis.

Table C1: Average Tradeability Indices by Category

Category	Imp./(Imp.+Output)		(Imp.+Exp.)/Output	
	Argentina	Uruguay	Argentina	Uruguay
Electronics, audio and video	47%	96%	223%	2380%
Cameras and accessories	62%	94%	794%	2363%
Cellphones and phones	65%	85%	486%	695%
Games and toys	55%	77%	158%	341%
Videogames	56%	79%	254%	459%
Music and movies	14%	3%	32%	8%
Music instruments	50%	78%	149%	341%
Health and beauty	33%	52%	91%	160%
Sports and fitness	37%	62%	100%	249%
Baby related	25%	47%	101%	164%
Clothing	16%	38%	30%	95%
Industries, office	36%	61%	139%	684%
Home, furniture, garden	26%	45%	99%	140%
Computers	69%	87%	1469%	1978%
Hobbies	39%	48%	109%	265%
Books and magazines	7%	6%	16%	11%
Jewelry	80%	89%	162%	342%
Car accessories	43%	80%	107%	149%
Appliances	22%	75%	51%	352%

Notes: This table presents average tradeability indices by broadest categories of goods on the online platform for Argentina and Uruguay. The first index is constructed as the ratio of sectoral imports to the sum of sectoral imports and output. The second index is constructed as the ratio of the sum of sectoral imports and exports to sectoral output.

Time series of GDP were obtained from national accounts of each country. Given the lack of monthly series of GDP, we interpolate quarterly data on GDP using cubic interpolation to obtain monthly series (results are unchanged if we use other monthly indicators of economic activity).

To construct the category-market CPIs for each country we use detailed CPI level data. The objective is to construct price indexes that represent the same markets as in the online platform. The *vehicles* price index is given by the CPI component "vehicles." For most countries this series is available for long periods and, in most cases, we can capture the acquisition price (i.e., exclude maintenance or other related costs). The *real estate* price index corresponds to the CPI component "rent." For most countries this series is available for long periods and captures the average cost of renting a real estate property. Finally, the *goods* price index is constructed by identifying various categories of the CPI index and aggregating them using their relative weight in the basket of consumption in each country. Goods categories included in this index are durable, and exclude the rent and vehicle categories considered before. Goods included in this category are, for example, house tools, electronics or clothes. For each country the level of detail of the publicly available CPI data[20] varies and, as a consequence, the detail at which we can identify the categories included in this index also varies.

When analyzing the relevance of currency choice for specific categories of goods in the Uruguayan CPI, we use monthly price indices from 1997 to 2010 produced by the national statistical agency (INE).

[20] This is considering a long enough period of time needed for our estimations.

D Representativeness Analysis

In this Appendix, we analyze the relevance of goods that are available for sale on the platform by analyzing microdata on buyers' consumption patterns from the Uruguayan household consumption survey (*Encuesta Nacional de Gastos e Ingresos de los Hogares*). This survey was conducted in 2005-2006 and contains detailed information on consumption at the good level for a representative sample of households. In this section, we discuss the representativeness of our analysis in terms of the types of goods available for sale on the online platform relative to the average household consumption basket.

Table D1 compares the types of goods included in the average household consumption basket (using data from the consumption survey) with the goods available on the online platform. In the second column, we show the share of total monthly expenditure households spend on broad categories of goods. These categories are the ones used officially when constructing the CPI. The third column presents the expenditure share in the average household consumption basket, including only types of goods that are also available for sale on the online platform. The last column simply reports the share of items available for sale on the platform as a function of the total number of items in each consumption category.

In terms of average expenditure shares, the goods included on the online platform cover almost a third of total average monthly expenditures. In particular, we have a good coverage in Apparel, Furniture and Home Appliances, and Culture and Recreation, i.e., mostly durable goods. As expected, we have almost no coverage of services and food items. Therefore, aggregate price dollarization would be lower in the aggregate, because food should be expected to be priced in local currency.

In addition, in another paper (Drenik and Perez, 2020), we use the historical data from the platform to show that the implicit inflation rate constructed from prices from the online data closely tracks the aggregate unofficial inflation in Argentina for the period 2008-12. Finally, Table D2 includes a list of other relevant websites in Latin America, where dollar pricing can be found.

Table D1: Representativeness of the Basket of Goods Sold on the Online Platform

Category	Share of total expenditure	Expenditure share on online-platform	Share of items on online-platform
Food and Non-alcoholic Beverages	23.0	0.00	0.00
Alcoholic Beverages and Tobacco	1.52	99.9	80.0
Apparel	4.12	95.3	93.0
Housing and Utilities	30.2	65.3	43.7
Furniture and Home Appliances	3.97	36.9	72.6
Medical Care	10.9	3.80	4.76
Transportation	8.48	5.13	9.09
Communications	4.16	10.1	12.5
Culture and Recreation	5.12	48.6	58.8
Education	1.40	0.00	0.00
Hotels and Restaurants	2.42	0.00	0.00
Other Goods and Services	4.56	22.2	32.0
Total	100.0	31.4	29.8

Notes: This table analyzes the representativeness of the data from the online platform by showing the fraction those goods represent in the average household consumption basket. Data on households' expenditures are from the national consumption survey from Uruguay (ENGIH) conducted in 2005-2006. The second column shows the average split of total expenditures between large categories (those used when computing the official CPI). The third column shows, for each category and overall, the average expenditure share for goods that are also available for sale on the platform. The last column shows the share of types of goods, within categories and overall, that are available for sale on the platform. Summary statistics were computed using household weights.

Table D2: Price Dollarization in Latin America: Other Websites

Country	Market	Website
Argentina	Real Estate	https://www.zonaprop.com.ar/
Argentina	Real Estate	https://www.argenprop.com/
Argentina	Real Estate	https://www.remax.com.ar/
Argentina	Real Estate	https://www.olx.com.ar/
Argentina	Vehicles	https://demotores.com.ar/
Argentina	Vehicles	http://www.deautos.com/
Argentina	Vehicles	https://www.autocosmos.com.ar/
Argentina	Vehicles	https://www.olx.com.ar/
Argentina	Vehicles	https://www.autofoco.com/
Peru	Real Estate	https://www.adondevivir.com/
Peru	Real Estate	https://www.laencontre.com.pe/
Peru	Vehicles	https://neoauto.com/
Peru	Vehicles	https://www.olx.com.pe/
Peru	Vehicles	https://peru.todoautos.com.pe/
Mexico	Real Estate	https://www.inmuebles24.com/
Mexico	Real Estate	https://www.vivanuncios.com.mx/
Mexico	Real Estate	https://www.remax.com.mx/
Uruguay	Goods	https://www.tiendainglesa.com.uy
Uruguay	Goods	https://www.devoto.com.uy
Uruguay	Goods	https://www.disco.com.uy/
Uruguay	Goods	https://www.geant.com.uy/
Uruguay	Goods	https://magiccenter.com.uy/
Uruguay	Goods	https://nelsonsobrero.com.uy/store/
Uruguay	Goods	https://www.multiahorro.com.uy

Notes: This table includes links to relevant websites in Latin American where dollar pricing is also present.

E Price Dollarization: Further Results

E.1 Variance Decomposition Analysis

To assess the role of sellers' and goods' characteristics, we carry out a variance decomposition analysis. Each listing in the data contains seller identifiers. Additionally, the majority of the listings include a narrow categorization of the good at level 3 in the category tree (see Section 3 for a description of the categorization of goods). Examples of good categories at this level include smart TVs, Apple smartwatches, soccer jerseys, strollers, mattresses, wallets, Playstation 4, and guitar amplifiers. We estimate the following linear probability model for each of the main countries in the data separately:

$$dollar^i_{s,c} = \alpha_s + \beta_c + \varepsilon^i_{s,c},$$

where $dollar^i_{s,c}$ is a dummy variable that equals one if the price of good i, posted by seller s in category c, is in dollars and zero if it is in local currency; α_s is a seller fixed effect; β_c is a good-category fixed effect; and $\varepsilon^i_{s,c}$ is the residual term. We restrict the sample to those sellers that post more than one listing.[21] We estimate the econometric model by OLS. We then compute the variance of the estimated seller and category fixed effects, and express them relative to the overall variance of the dependent variable. We report the results in the first two columns of Table E1. Both seller and good characteristics are relevant in explaining currency choices of prices. On average, seller fixed effects explain 36% of the variation in the currency choice of prices, and category fixed effects explain 21%. There is significant heterogeneity across countries: In Mexico, most of the explained variation is associated with seller fixed effects, while in Peru, both sellers and good-categories explain the same amount of variation. Finally, we also estimate the regression including category-seller fixed effects (column 4 of Table E1). The explained variation increases significantly, ranging between 50% to 90% in each country.

E.2 Price Stickiness

In this section, we document how often and by how much prices change. In the main dataset, we observe the price of each listing on a daily basis and can therefore compute the frequency

[21] Conditioning on sellers that post multiple listings, the average number of listings per seller is 31. Similarly, the average number of listings within categories at level 3 is 2,693.

Table E1: Currency Choice of Prices: Variance Decomposition Analysis

Country	Category FE	Seller FE	Cat.-Seller FE	# Obs.	# Cat.	# Sellers
Argentina	20%	24%	71%	1655986	189	160799
Mexico	2%	37%	50%	2430439	1948	94379
Uruguay	26%	43%	85%	916648	1730	52390
Peru	36%	41%	87%	555770	1281	35290

Notes: This table presents the results of variance decomposition analysis of the currency choice of prices. Each regression is estimated with OLS using data from each country separately. Sellers that only post one listing are excluded from the regression. Results are reported as a fraction of the overall variance of the dependent variable. The last three columns report the number of observations by group.

and magnitude of price changes by currency. Table E2 shows various summary statistics regarding price changes of goods, vehicles, and real estate in the main countries. The first two columns show the frequency of price changes; that is, the average share of prices that change on a daily basis. There is significant heterogeneity across types of goods and also across countries. The frequencies of price changes range from 0.1% to 2.5% in most countries and types of goods. Implied durations of prices in months are reported in columns 3 and 4.[22] The last four columns of Table E2 report the median size of price changes, which range between 7% and 20% for price increases and -7% and -15% for price decreases. These magnitudes are in the range of results from previous studies for the US (e.g., Bils and Klenow (2004) and Klenow and Kryvtsov (2008)).

In spite of the observed large heterogeneity, we observe regularities when we compare the degree of price stickiness by currencies. With few exceptions, the frequency of price changes is larger for prices in local currency than for prices in dollars. This is consistent with the fact that inflation in local currency is higher than inflation in foreign currency in all of the countries in our sample. Finally, changes in the currency of denomination of prices within listings are very rare (results not shown). The two largest daily probabilities of a change are found in the market for vehicles in Argentina and Uruguay, at 0.26% and 0.07%, respectively (with implied durations of 1.05 and 3.9 years).

[22] In this analysis, we restrict the sample to listings that had at least one transaction and that had at least 60 days of data. Table E3 replicates the analysis by including all listings with at least 60 days of data, irrespective of whether they had a transaction or not. Assuming a constant hazard rate λ of a price change, the daily probability of a price change is equal to $f = 1 - e^{-\lambda}$. Thus, the average duration in months is given by $(1/\lambda)/30 = (-1/\ln(1-f))/30$.

Table E2: Price Stickiness by Currency: Listings with Positive Transactions

	Freq. Price Changes		Implied Duration		Share Price Inc.		Med. Price Increase		Med. Price Decrease	
Country	Local Cur.	Dollar	Local Cur.	Dollar	Local Cur.	Dollar	Local Cur.	Dollar	Local Cur.	Dollar
Goods										
Argentina	.%	.%	.	.	.%	.%	.%	.%	.%	.%
Mexico	1.07%	0.20%	3	17	48%	59%	9%	10%	-9%	-14%
Uruguay	0.70%	0.54%	5	6	58%	53%	12%	10%	-14%	-11%
Peru	0.37%	0.13%	9	26	40%	39%	14%	17%	-14%	-14%
Vehicles										
Argentina	1.86%	0.71%	2	5	71%	31%	8%	7%	-8%	-7%
Mexico	0.67%	0.18%	5	19	18%	31%	6%	11%	-5%	-11%
Uruguay	1.38%	0.51%	2	7	39%	17%	22%	11%	-11%	-8%
Peru	1.86%	2.57%	2	1	0%	2%	.%	4%	-17%	-5%
Real Estate										
Argentina	0.43%	0.19%	8	17	72%	26%	12%	8%	-11%	-7%
Mexico	0.14%	0.06%	24	53	40%	35%	11%	13%	-10%	-13%
Uruguay	0.31%	0.15%	11	22	13%	32%	9%	10%	-8%	-10%
Peru	1.59%	0.75%	2	4	75%	36%	22%	10%	-3%	-7%

Notes: This table presents statistics on price stickiness for each country and type of market (goods, vehicles, and real estate), by currency. The sample is restricted to listings that had at least one sale and 60 days of data. The average daily frequency of price changes is the fraction of listings that changed price in a given day. The average implied duration (in months) is equal to $(-1/ln(1-f))/30$, where f is the daily frequency of price changes. The last six columns show the share of price changes that result in price increases, and the mean absolute sizes of (log) price increases and decreases.

Table E3: Price Stickiness by Currency: All Listings

	Freq. Price Changes		Implied Duration		Share Price Inc.		Med. Price Increase		Med. Price Decrease	
Country	Local Cur.	Dollar	Local Cur.	Dollar	Local Cur.	Dollar	Local Cur.	Dollar	Local Cur.	Dollar
Goods										
Argentina	.%	.%	.	.	.%	.%	.%	.%	.%	.%
Mexico	3.34%	0.16%	1	21	44%	55%	7%	14%	-7%	-17%
Uruguay	0.72%	0.27%	5	12	56%	54%	11%	10%	-13%	-12%
Peru	0.29%	0.09%	11	37	39%	46%	14%	16%	-14%	-15%
Vehicles										
Argentina	2.05%	0.74%	2	4	71%	32%	9%	7%	-8%	-7%
Mexico	0.72%	0.14%	5	23	19%	30%	7%	11%	-5%	-12%
Uruguay	1.22%	0.54%	3	6	49%	20%	20%	10%	-16%	-8%
Peru	0.96%	1.41%	3	2	17%	14%	14%	12%	-8%	-6%
Real Estate										
Argentina	0.60%	0.19%	6	18	78%	31%	13%	9%	-14%	-8%
Mexico	0.13%	0.07%	25	51	45%	42%	11%	14%	-10%	-14%
Uruguay	0.34%	0.19%	10	18	22%	40%	16%	10%	-10%	-10%
Peru	0.73%	0.65%	5	5	35%	24%	22%	11%	-17%	-9%

Notes: This table presents statistics on price stickiness for each country and type of market (goods, vehicles, and real estate), by currency. The sample is restricted to listings with at least 60 days of data. The average daily frequency of price changes is the fraction of listings that changed price in a given day. The average implied duration (in months) is equal to $(-1/\ln(1-f))/30$, where f is the daily frequency of price changes. The last six columns show the share of price changes that result in price increases, and the mean absolute sizes of (log) price increases and decreases.

F Structural Interpretation of Pass-through Regressions

This appendix shows that the pass-through regressions on quantities can have a structural interpretation, under which the estimated parameters reflect the elasticity of demand. We analyze a generalized version of the demand structure of the model presented in Section 2. For simplicity, we isolate from dynamic considerations and consider a static environment. The dynamics of pass-through to quantities sold can be generated by slow adjustments of demand to price changes due to, for example, search frictions in online markets (see, for example, Ellison and Ellison (2009)).

Consider a representative consumer whose preferences are given by the following nested CES function:

$$U = \left(\int_J \psi_j(e)^{\frac{1}{\sigma}} \left(\sum_{i=1}^{N} \psi_{ij}^{\frac{1}{\sigma}} C_{ij}^{\frac{\epsilon-1}{\epsilon}} \right)^{\frac{\sigma-1}{\sigma}\frac{\epsilon}{\epsilon-1}} \mathrm{d}j \right)^{\frac{\sigma}{\sigma-1}},$$

where σ is the elasticity of substitution across good categories $j \in J$, ϵ is the elasticity of substitution within goods of a category j, C_{ij} denotes consumption of good i in category j (henceforth, good ij), ψ_{ij} are demand preference shocks associated with good i in category j, and $\psi_j(e)$ are preference shocks associated with category j. We allow for good-category preference shocks to depend on the (log of) exchange rate e. The dependence of ψ_j on e captures the fact that households that have different exposures of their incomes to the exchange rate can have different ψ_j. For example, this could capture a situation in which richer households have a higher elasticity of income to the exchange rate and stronger preferences for durable goods than poorer households. As we show below, our econometric strategy can allow for a differential impact of e on ψ_j, and still estimate ϵ.

The budget constraint of the household is given by

$$\int_J \sum_{i=1}^{N} P_{ij}(e) C_{ij} = W(e).$$

where $P_{ij}(e)$ is the price of good i in category j in local currency and $W(e)$ is household income (or wealth) in local currency, both of which are allowed to vary with the exchange rate. Demand for good ij is given by

$$C_{ij} = \psi_{ij}\psi_j(e)\left(\frac{P_{ij}(e)}{P_j(e)}\right)^{-\epsilon}\left(\frac{P_j(e)}{P(e)}\right)^{-\sigma}\frac{W(e)}{P(e)}, \tag{30}$$

where P_j and P are the category j and aggregate price indices, respectively, and given by

$$P_j(e) = \left(\sum_{i=1}^{N}\psi_{ij}P_{ij}^{1-\epsilon}(e)\right)^{\frac{1}{1-\epsilon}},$$
$$P(e) = \left(\int \psi_j(e)P_j^{1-\sigma}(e)\right)^{\frac{1}{1-\sigma}}.$$

Consider now a depreciation in the exchange rate of $\Delta e > 0$, and denote $x = \log X$ for any variable X. Given our empirical findings that in the short-run, prices are sticky and pass-through is one for prices in local currency and zero for prices in dollars, we have that

$$\Delta p_{ij} = \Delta e \mathbb{1}\{curr_{ij} = d\}, \tag{31}$$

where $\mathbb{1}\{curr_{ij} = d\}$ is an indicator function that equals one when the currency of good ij is the dollar. Log-differentiating (30) and using (31) yields

$$\Delta c_{ij} = -\epsilon\Delta e\mathbb{1}\{curr_{ij} = d\} + \left[\Delta\psi_j(e) + (\epsilon - \sigma)\Delta p_j(e) - (1-\sigma)\Delta p(e) + \Delta w(e)\right]. \tag{32}$$

It is straightforward to see that the second term in (32) is captured by the category-time fixed effects α_{jt} included in the regression specification (7). This implies that the estimate of $\sum_{k=1}^{n}\theta_k$ in (7) corresponds to an estimate of the elasticity of demand ϵ. The key identifying assumption that we make to be able to estimate this elasticity is that ψ_{ij} does not depend on e. In other words, we assume that, within goods of a given category j, the exchange rate does not differentially affect their demand. We consider this to be a realistic assumption, since the identified categories in the data correspond to very narrowly defined sets of goods (see Table B.4).

References

United Nations (2008): "International Standard Industrial Classification of All Economic Activities (ISIC), Rev. 4," *New York: United Nations.*