The Demand Side of Firm Growth: Evidence from Mexico*

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Abstract: When information frictions prevent consumers from discerning the quality of products, they may prefer to buy from firms with an established reputation. This can hinder the growth of small or new firms with high-quality goods, negatively contributing to the aggregate output growth. This paper investigates how uncertainty about product quality differentially affects domestic and international firms in Mexico, where the latter firms tend to be larger in size. In the Mexican consumer goods industry, there exist concerns about product quality. Leveraging barcode-level consumption data, I document the fact that consumers pay a high price premium for goods carrying global brands, controlling for observed quality, reflecting a demand for unobserved quality: despite this price premium, foreign firms dominate many product markets. This has consequences on domestic firm growth. I document the following novel facts about this industry: 1) domestic firm growth is driven by surviving goods rather than new goods; 2) domestic goods have slower and longer lifecycles than foreign goods; 3) the extensive customer margin is key to growth for both types of firms; 4) domestic firms, however, depend relatively more on the intensive margin for growth; and 5) new customers of older goods are poorer than those of new goods, only in the case of domestic firms. I rationalize these findings by developing a model of product choice under quality uncertainty. The possibility of learning from others makes the most price-sensitive customers delay purchasing new domestic products, driving down domestic firm profits. I provide empirical evidence consistent with the model's mechanisms, which highlight the importance of individual learning, product quality uncertainty, and price-sensitivity.

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Keywords: growth; quality uncertainty; international competition; learning; consumer goods

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1 Introduction

A prevalent feature in developing countries is the absence or the lack of enforcement of quality regulation, which means customers cannot be certain they are buying a high-quality product. As a result, it may be difficult for firms based in developing countries to find customers who value their products, even if they actually are of high quality.[1] Firms may try to signal themselves as high-quality through advertising, branding, certifications, etc., but Bai (2018) has shown that signaling mechanisms can be too costly in certain contexts.

Globalization increases the set of competitors firms must contend with.[2] In developing countries, multinational corporations (henceforth MNCs) headquartered in high-income countries dominate many product markets. It may then be very difficult for relatively unknown domestic firms to acquire a reputation over time when competing with long-established, high-reputation MNCs, as analyzed by Schmalensee (1982).[3]

In this paper, I ask how uncertainty about product quality, combined with the presence of typically large, historical foreign firms, explains the size and growth patterns of typically small domestic firms. I study this question in the context of the Mexican consumer packaged goods sector, which represent 20% of households' expenditure. Uncertainty about quality may be a critical issue in this sector. One reason is that while ensuring food quality is essential for health reasons, some firms may not be meeting the standards achieved in rich countries. The United States' Food and Drug Administrations often recalls product that were exported from Mexico to the United States, a lower bound for the number of (potentially unreported) issues with product that did not leave the domestic market.[4] The Mexican authority for food safety, Cofepris (Comision Federal para la Proteccion contra Riesgos Sanitarios), regularly updates the official norms food manufactures must abide by in an effort to curb quality issues.

I first establish a novel fact: Foreign firms in Mexico are able to capture a large market share despite charging a price premium. Controlling for a range of product characteristics, global brands charge on average a 20% price premium. Despite this higher price, the aggregate market share of foreign firms is far above 50% for most product categories. This is remarkable given that 42% of the population lives under the national poverty line. This suggests that there are consumers who are willing to pay a higher price for high-quality products, a potential source of growth for high-quality domestic firms if they could harness this demand. Last, conditional on having several products, Mexican firms release less new goods than foreign firms proportionally to their size, a possible consequence of the lack of incentive or ability to invest in product innovation, further reinforcing the problem of lack of quality.

I answer this question by leveraging a rich barcode-level dataset covering the universe of consumer-packaged goods in Mexico from 2010 to 2015. I start by establishing five novel facts

[1] See Verhoogen (2021) for a review of the literature on barriers to firm-level upgrading

[2] Globalization also increases the size of the market firms have access to. But Goldberg and Reed (2020) argue that ultimately firm sales must also come from the middle-class consumers at home. Some recent papers have proposed strategies to give firms access to this additional demand. For example, Atkin et al. (2017a) match rug makers in Egypt to importers in high-income countries.

[3] In the firm-to-firm sector, the presence of large buyers may help small domestic firms as shown by Alfaro-Ureña et al. (2019) Hjort et al. (2020) teach firms how to answer tender calls for large firms or governments.

[4] For a list of recent examples, see this article by digital media platform Sin Embargo and this public health article.

based on observing the sales of the 3985 firms selling goods to the households in the dataset. First, using a data-driven definition of new goods, I decompose the sales of firms in each year between sales of new goods and sales of surviving goods. By comparing the "new goods" and "surviving goods" sales of the same firm over time, I find that for foreign firms operating in Mexico, firm-level growth comes roughly equally from new goods than from surviving goods, while Argente et al. (2019) find that growth comes from the sale of new goods in the United States. Moreover, I find that for domestic firms a very large share of sales growth comes from the growth of surviving goods sales.

Second, at the product level, when foreign firms introduce new goods, sales grow for a short period after the introduction of the good and then decline for a long period, as demand is cannibalized by newer products of the same firm or "stolen" by other firms. This has been shown in the context of the United States by Argente et al. (2019). When Mexican firms introduce new goods, they start off by selling considerably less than comparable new foreign products. But, conditional on surviving, sales grow and stay higher than in the initial quarter for up to two years. This suggests that Mexican firms are able to retain demand and attract new demand for their products as they age.

Third, for both types of firms the key driver of sales growth is growth in the number of customers, as opposed to growth in the number of units sold to each customer or growth in the sales generated per unit. This fact helps us interpret the rapid demand depletion observed for foreign products as customers who were buying the goods when they are first released, being attracted to newer products by the same firm or by other firms as the products age. By contrast, the sustained demand observed for domestic products reflects either the persistence of the customers who first started buying the goods or the arrival of new customers purchasing the goods as they age.

Fourth, I show that in order to grow their customer base, domestic firms depend relatively more on the intensive margin of product markets — growing the number of customers they sell each product to —, as opposed to the extensive margin — growing the number of products they sell. This suggests that the first-order problem faced by domestic firms is not that their products do not match the taste of domestic customers, but potentially that they must overcome barriers to convince customers that they will appreciate each of their existing products.

Fifth and last, I show that the new customers of domestic products that have survived several quarters are poorer than the new customers buying domestic products which have just been released. By contrast, the new customers of foreign products that have survived several quarters are not different than the customers of these same foreign products when they were new. Together with the second fact about the domestic product life-cycle, this finding suggests that customers who face stricter constraints in their consumption decisions do not buy new domestic products immediately, but instead wait until these products survive a certain age before purchasing them.

Based on these facts, I propose a model of consumer decision that generates equilibrium outcomes matching these facts. In this model, consumers face uncertainty about product quality. Consumers who have a tighter budget constraint are less likely to experiment with a product of unknown quality, conditional on price. If it is possible to learn from others, there is a positive option value of waiting until other, less constrained individuals experiment with the product and reveal whether they liked it or not. This generates a delay in product adoption, hurting firms' profits.

I test the implications of the model in three different ways. To begin, I show evidence of individual learning. I do this by measuring the importance of brand experience in explaining consumers' decisions about purchasing products they haven't tried before. I show that individual exposure to a brand is highly predictive of future purchases of goods from that brand. Moreover, this effect is higher for domestic brands than global brands, despite domestic brands being less successful on average. Then, I show evidence of the uncertainty margin. I do this by exploiting the heterogeneity in product types. For products for which quality is more salient, such as infant formula, prior experience with a brand has a larger effect on the probability to purchase more products. Finally, I show that learning is more important for individuals who are more budget constrained: the predictive power of brand exposure is much higher for households in the bottom half of the expenditure distribution.

Section 2 describes the literature this paper aims to contribute to. Section 3 describes the data and the setting. Section 5 discusses the five dynamic facts I establish. Section 6 explains the conceptual framework I use to think about our results. Section 7 shows evidence of the mechanisms at work. Section 9 concludes.

2 Literature

Akerlof (1970) showed that when buyers cannot tell apart high-quality goods from low-quality goods, both types will be pooled under the same price, leading to unraveling and ultimately large welfare costs. Buyers and sellers must therefore rely on strategies to signal and identify high-quality goods. A well-studied strategy, relational contracts, is not really possible in the retail context (see Macchiavello et al. (2015) for example). Warranty schemes (Shimp and Bearden (1982)) may work for durable goods but not for non-durables, while certification schemes are not always welfare increasing (Dranove and Jin (2010), Bai (2018)). This paper contributes to thinking about how reputations can address asymmetric information.

Shapiro (1983) shows that if consumers can learn about quality over time, it is possible for firms to establish a reputation for quality and sell high-quality goods for a premium. A recent example, welfare-improving example is Bennett and Yin (2019). However, Bronnenberg et al. (2015) show that more informed shoppers (such as pharmacists for drugs, and chefs for groceries) are less likely to buy branded products, suggesting that a sizable share of the brand premium is due to a lack of information. The underlying hypothesis in this paper is that the MNC price premium may be "too high", reflecting frictions.[5]

Reputations can also be collective (Tirole (1996)), including at the national level. The marketing literature has studied the effect of Country of Origin on consumers' willingness to

[5]The premium could also be due to a form of status associated with foreign brands (see for example Orlove (1997)), Batra et al. (2000)). This would mean that there is no such thing as "too high" a premium, as long as it generates utility for consumers. I believe it is less likely in this context of at home consumption. Moreover, the fact that the price premium fades over time as documented later on suggests that it is at least partly due to frictions.

pay for goods, although few use prices as outcomes,[6] see Papadopoulos and Heslop (1993) for a thorough review. Generally, consumers project a country's historic advantage in a product line (for example, German firms make good cars and French firms make good wines). Cagé and Rouzet (2015) shows that this can translate to a country's vertical reputation of quality. Bai et al. (2019) have shown that being associated with a country that has a bad reputation can harm an individual firm. On the other-hand, buyers in developing countries generally value products imported from or made by MNCs headquartered in high-income countries[7].

This perception premium can translate into a price premium, although it has not been well documented. Faber (2014) shows that imported inputs are correlated with higher prices of goods produced in Mexico. Ge et al. (2015) uses customs data from China to show that foreign MNC enjoy a higher export price than Chinese firms, controlling for productivity, which they attribute to quality. However, they do not observe product-level characteristics. In this paper, I turn to the consumer side, and enjoy a very high level of detail about product characteristics. Using scanner data, Bems and Di Giovanni (2016) find a 28% import premium for consumer goods in Latvia. This paper is to my knowledge the first to estimate a precise foreign price premium for consumer packaged goods in a developing country.

This paper also contributes to thinking about the role of of advertising and marketing in helping firms to signal individual quality (see Bagwell (2007) for a review). Using survey data on Pakistani soccer ball manufacturers, Atkin et al. (2017b) show that that the firms who charge the highest markups are not necessarily the most productive ones, but the ones that make the most marketing efforts, for example by participating in international trade fairs. In a randomized controlled trial, Hjort et al. (2020) show that teaching firms marketing skills can expand the market they have access to, in particular towards large buyers, and thus enhance growth possibilities.

The trade literature has looked at the implications of the impact of marketing efforts on firms' ability to sell. Arkolakis (2010)' seminal paper shows that the convex cost of reaching additional customers in a given market can explain the puzzle that despite fixed costs to exporting in an additional country, many firms export small volumes in each destination. Recently, papers using scanner (Hottman et al. (2016), Afrouzi et al. (2020)) and credit card data (Einav et al. (2021)) have shown that firms' reputation are an important driver of sales. Marketing efforts a key input to that reputation, although Einav et al. (2021)'s model suggests it may crowd out innovation efforts. This paper suggests that marketing spending may help support an industrial policy aiming to help the domestic sector grow.[8]

I contribute to understanding the life-cycle of products. Argente et al. (2019) study

[6] The closest I could find was Hulland et al. (1996)'s study. They collected the prices of goods illegally imported to the Philippines and regressed them on their country of manufacture, controlling for the multinational. They find a 55% to 65% import price premium, even for products imported from low-income countries, suggesting that part of their finding might be attributed to the peculiarity of the environment.

[7] See the India Times's 2015 article about consumer packaged goods; See also IFPRI's note on rice in Ghana, Ragasa et al. (2014) to understand why this may be a concern

[8] The internet may introduce cheaper alternatives for firms to market their products (see Chen and Wu (2020) for example). While e-commerce is still out of reach for many small firms in developing countries, it is an avenue for growth. In this paper, I study a market yet relatively untouched by the Internet, but which will be increasingly so: in 2020, 25% of Mexican consumers have bought groceries online up from 13% in 2017 and less than 3% in 2014, OECD, ICT Access and Usage by Households and Individuals

the product life-cycle of consumer goods. They show that product turnover is high and firms must constantly reinvent their product scope in order to avoid business stealing, even though this strategy increases cannibalization. Perla (2019) proposes an alternative model to explain these life-cycles. His central idea is that customers may be "aware" of some products and not others. This means that firms have more market power than what the nominal number of competitors suggests. As products age though, customers learn about their existence through social networks. A relevant review of empirical work estimating social learning effects is Mobius and Rosenblat (2014), with some of the most famous ones Foster and Rosenzweig (1995) and Duflo and Saez (2003). Although it is not possible to estimate social learning effects empirically here due to the structure of the data, this paper contributes to the theoretical literature on social learning.

Last, this paper contributes to understanding how trade, through the presence of MNCs, affects the welfare of consumers in developing countries. Fajgelbaum and Khandelwal (2016) show that trade is generally pro-poor because it decreases the price of goods that poor consumers spend a relatively higher share of their budget on. However, using more detailed consumer survey data from India, Atkin (2013) shows that because preferences change slowly, trade-induced decreases in prices may not increase poor consumers' calorie intake as much as one would expect. Using barcode-equivalent data from Mexico, Atkin et al. (2018) further show that the arrival of Walmart in new areas is relatively more beneficial for higher-income consumers. However, they do not observe the origin of the goods consumed, which I do. Using information about the origin of goods, Atkin and Donaldson (2015) show that intra-national trade costs might limit the ability of consumers in remote area to benefit from trade. However, they are only able to look at about a dozen different goods across three countries. In this paper, I have access the precise origin of the firms supplying the goods consumed in the entire urban Mexico, offering a different angle on how to design pro-poor trade policies.

3 Data and Setting

In this section, I describe the three primary data sources containing information on the Mexican consumer goods sector, covering the period of January 2010 to December 2015. After describing each source in detail, I highlight the relevant features of the market.

3.1 Data

The main source of data is a rotating household panel shared by Kantar World Panel[9]. Households are visited twice a week to obtain a complete consumption diary about all of the packaged goods purchased for at-home consumption. I observe[10] 7182 distinct households per month on average and a total of 15750 unique households from all 32 states of Mexico.[11] The sample is designed to represent metropolitan areas (collection of municipalities) in Mexico with more

[9] Kantar World Panel is an international company that operates in more than 50 countries They specialize in the collection of household consumption data for marketing and sales strategy purposes. For more information on the data-sharing agreement, see Aguilar et al. (2021).

[10] Given the observations I exclude because the purchases are not identified by their manufacturer.

[11] On average, households stay in the panel for 3.4 years. I observe 1191 households on all 72 months.

than 50,000 individuals.

The panel provides information on the purchases of all packaged goods made over time, except for liquor and tobacco. For each purchase, I observe the transaction date, several characteristics, the price, the units purchased, the type of the store where the purchase was made,[12] whether the product was subject to special promotions, and the payment method. Importantly for the rest of the paper, I also observe the name of the manufacturer of the good. For soft drinks purchases for example, the product characteristics would include whether the drink is "diet", the flavor, the content size and the package type (e.g. can or plastic bottle). It would then indicate "Coca-Cola FEMSA" if the item was produced by the Coca-Cola subsidiary in Mexico. I mostly do not observe products purchased in bulk or by weight such as fresh fruits and vegetables, meat and fish, etc. Products that are described as being purchased in bulk (such as tortillas, a staple item for Mexican households) or for which the manufacturer is not identified are dropped.[13]

The panel also contains economic, demographic and geographic information about each household. I observe these variables at the yearly level. They include information about household members' age, gender and occupation. I also observe asset-like characteristics about households: I know whether they have a fridge, a TV, and other appliances. I observe a few dwelling characteristics. Last, I observe a socioeconomic status (SES), which is computed based on households' assets, the dwelling characteristics, the head of household education and purchasing power, as computed by the Mexican Association of Market Intelligence Agencies (AMAI).[14] I observe five values for the SES. Geographic variables include the neighborhood of residence.

The second source of data is the yearly updated directory of private establishments (Directorio Estadístico Nacional de Unidades Económicas or DENUE) conducted by the Mexican national statistical institute, INEGI. DENUE was first created in 2010 based on the 2009 Economic Census. Since then, DENUE has been used as a sampling frame for business surveys.[15] Although this dataset provides the exact addresses of all 5478689 establishments listed, the KWP dataset only lists one of the names of the firm, which may be multi-establishment. I therefore merge this name with either the given or the official name of an establishment in the administrative dataset, but cannot tell which establishment actually corresponds to each good. This dataset is important because it helps us narrow down our definition of the "firms" I study in this paper.

The third source of data is the yearly updated register of foreign investment (Registro Nacional de Inversiones Extranjeras or RNIE) which is maintained by the Mexican Economic Secretary (Secretaria de Economia). Firms based in Mexico that receive foreign capital directly (as opposed to through stock) are listed there. There are 65810 firms in total. I match the name of the manufacturers collected by Kantar with the names of firms listed in this list, which defines their status as a foreign firm and in the case of the latter gives us the origin of the

[12] I observe the name of the retail chain if the purchase was made at a retail chain. If not, I observe whether the purchase was made in a store that does not belong to a chain or in an open-air market.

[13] For this reason, I am unable to do the analysis on "unbranded goods" as unbranded goods are not identified by their manufacturer.

[14] See AMAI'swebsite for more explanation

[15] See a commentary from the American Statistical Association

foreign investment.

3.2 Descriptive Statistics

Households I summary the characteristics of the panelists in Table B.1. To see how they compare to a representative data, I also describe these characteristics for the households surveyed in the expenditure and income survey of households, ENIGH, conducted by the national statistical office, INEGI, in 2010. Households in the Kantar data appear to be slightly larger than households in the ENIGH data and slightly better off in terms of assets, but overall they are comparable.

Goods I observe 66059 different products over 82 categories. For each product, I observe between one and seven characteristics such as brand, flavor, color, size, number of units in the package etc. This description is similarly precise as the one available in better known datasets such as Nielsen which report at the barcode level. In the baseline specification of the empirical analysis, I will refer to these goods defined by Kantar under a product identifier as "barcodes".

Firms These barcodes are manufactured by 3985 different firms, 94% of which receive no foreign direct investment. The few firms who do are much larger as shown in Figure A.1, which plots the distribution of annual total expenditure panelists made on each firm. Among foreign firms, 49% receive FDI from the USA.[16] The rest of the foreign investment is from 30 different countries, which limits our ability to do separate analysis by country of origin.

4 Static Stylized Facts

4.1 The foreign price premium

In Appendix Table B.2, I show the import price premium measured on rice from widely used consumption surveys, the Living Standard Measurement Surveys of the World Bank. Very few questionnaires information for both a domestic item and its imported version. Even scanner datasets in both high-income and middle-income countries do not have the origin of the good. I provide the first estimate of import price premium based on scanner data in developing countries. Foreign firms also charge much higher prices and enjoy larger market shares than domestic firms. To show this, I run the following regressions within each product category:

$$y_{i,g,t} = \alpha + \beta \text{Foreign}_i + \zeta_{gt} + \mu_i + \epsilon_{i,g,t} \tag{1}$$

where I regress barcode i's price y observed in city g in month t on a dummy for whether the manufacturer is foreign or not and control for a set of city and time fixed effects ζ_{gt}.

In the baseline specification, I control for the product category that barcode i belongs to μ_i. I show two other specifications, one controlling for the subcategory of product (when mentioned) and one controlling for this and the size of the package sold. Figure 1 shows the Foreign coefficients β obtained for the largest 20 product categories, based on what characteristics are included as controls. In the baseline specification I only control for product category and city

[16] This is similar to the share of US investment in the total foreign investment inflows received by Mexico over the last 20 years. Author' calculation based on the data published by the Secretaria de Economia.

	Log price					
	(1)	(2)	(3)	(4)	(5)	(6)
MNC	0.164	0.164	0.158	0.169	0.189	0.205
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
City by month FEs	6011	6011	6011	6011	6011	6011
Product FEs	180	180	10912	16647	23635	26397
Volume control	No	Yes	Yes	Yes	Yes	Yes
R2	0.53	0.87	0.91	0.92	0.93	0.94
N	43759653	43759369	43758021	43697214	42445758	37548230

Table 1: MNC price premium

	Log price					
	(1)	(2)	(3)	(4)	(5)	(6)
MNC HQ low-income	0.237	0.096	0.082	0.092	0.105	0.125
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
MNC HQ high-income	0.162	0.167	0.163	0.175	0.198	0.216
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
City by month FEs	6011	6011	6011	6011	6011	6011
Product FEs	180	180	10912	16647	23635	26397
Volume control	No	Yes	Yes	Yes	Yes	Yes
R2	0.53	0.87	0.91	0.92	0.93	0.94
N	43759653	43759369	43758021	43697214	42445758	37548230

Table 2: MNC price premium by origin of FDI

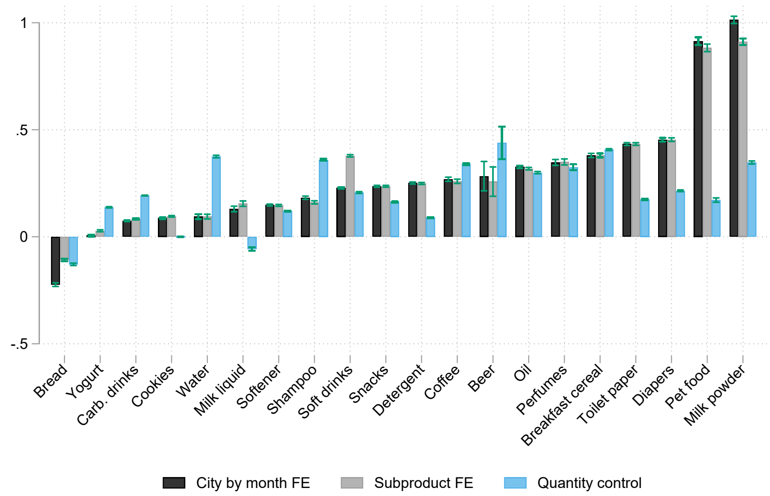

Figure 1: Foreign price premium

Notes: Figure reports the coefficient obtained from the purchase-level regression where a dummy that turns on if the product is sold by a foreign firm and characteristics fixed effects are regressed on the log price of the product. I repeat this regression three times for each of the top 20 categories in the dataset. Each regression uses incrementally additional characteristics as controls, which are described in the legend (grey and blue coefficients are obtained from regressions that also have city-by-month and and subproduct fixed effects, respectively). 95% confidence intervals are reported using the green bars. Products are sorted according to the size of the coefficient obtained in the first regression.

and time fixed effects, while in the second regression I control for a narrower product category and in the third regression I use city and time fixed effects, product subcategory, and size of the unit. Almost all the coefficients are positive, which I interpret as the "Foreign price premium". The Foreign price premium can be very large, up to 100% for the milk powder category, which is due both to the subsidized price of the domestic products sold by public establishments such as LICONSA and the importance of quality of products such as infant formula.

I run a similar regression for market shares in each product category:

$$y_{k,t} = \alpha + \beta \text{Foreign}_k + \vartheta_t + \epsilon_{k,t} \tag{2}$$

except now i is a firm and t is a year. I look at market shares defined in terms of sales, volume, and quantity (typically leveraging the information given by KWP about the content of each unit, usually in milliliters or grams depending on the nature of the product - since here the analysis is within product categories, I don't think there's a risk of bias). Figure 2 shows the

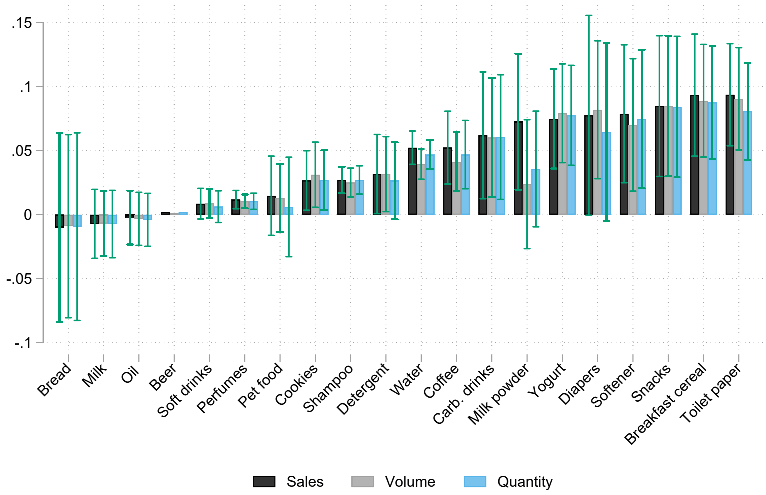

Figure 2: Foreign share premium

Notes: Figure reports the coefficient obtained from the firm-product-category-level regression where a dummy that turns on if the firm is foreign and year fixed effects are regressed on the market share of the firm in that product category. I repeat this regression three times for each of the top 20 categories in the dataset. Each regression uses a different definition of the market share, which are described in the legend. 95% confidence intervals are reported using the green bars. Products are sorted according to the size of the coefficient obtained in the first regression.

Foreign coefficients β obtained for the largest 20 product categories. All but four coefficients are positive, which I interpret as the "Foreign share premium". I point out the correlation between the negative coefficients observed for the sectors of milk, beer and bread with the existence of three very large Mexican firms in these sectors (Lala, Modelo and Bimbo respectively which are themselves MNCs, based in Mexico). The one for milk is further linked to the importance of a public establishment, LICONSA,[17] which sells milk to 18% of urban households. Further, I remark that the negative share premia for bread, milk and beer are coincidental with the smaller price premia for these product categories, emphasizing the idea that in the categories for which

[17] See Jiménez-Hernández and Seira (2021) for an assessment of government's role in milk provision.

there is no domestic powerhouse that is trusted, consumers turn to foreign firms which have proven their ability to deliver quality in other markets.

When looking at the rate of introduction of new goods, domestic firms appear to introduce slightly more new goods than foreign firms as shown in Columns (1)-(3) of Table 2.

	Share new products					
	(1)	(2)	(3)	(4)	(5)	(6)
Mexican	0.046	0.035	0.041	-0.046	-0.047	-0.037
	(0.012)	(0.013)	(0.013)	(0.007)	(0.007)	(0.007)
Firm sales, mMXN		-0.025	0.017		-0.004	-0.003
		(0.006)	(0.009)		(0.003)	(0.005)
Number of old varieties			-0.000			0.000
			(0.000)			(0.000)
Firm leader in category			-0.062			-0.013
			(0.034)			(0.017)
Category FEs	No	No	Yes	No	No	Yes
Baseline share (foreign)	0.22	0.22	0.22	0.16	0.16	0.16
N	12127	12127	12126	10008	10008	10008
R2	0.06	0.06	0.12	0.01	0.01	0.06

Table 3: Firm-level new goods introduction rate

Notes: Table reports the firm-year level regression of a dummy for whether the firm is Mexican, the firm sales in million MXN, the number of not new varieties, firm fixed effects and other firm-level characteristics described in the table, on the share of new products among the total number of products the firm has in a given year. The first three columns show all firms I have data for. Columns (4), (5) and (6) only show firms that sell at least one not new good in the year of observation. Standard errors are reported in parenthesis.

However, this result may be driven by the size heterogeneity between Mexican firms and MNCs: firms that do not have a product that is not new have a 100% new products rate. Therefore, in Columns (4)-(6) of Table 2 I focus on firms that sell at least one good that is not new in th year of observation. I find that the rate of introduction of new goods is smaller, at only 16% for foreign firms on average, and is smaller for Mexican firms, by about 3.7 percentage points. This foreshadows the implications of our model: if certain firms face difficulties finding customers for the same underlying level of quality, they will have less ability to invest in quality and less incentive to do so, reinforcing the prevalence of low quality products in the market.

5 Dynamic Facts

In this section, I leverage the rich data about consumer goods and establish a series of five novel facts about the dynamics of demand faced by domestic and multinational companies in Mexico.

5.1 Domestic firms grow relatively more through surviving goods

I follow Argente et al. (2019) who use scanner data to study the life-cycle of products in the United States. I decompose a firm's growth rate into the sum of a "new products" component and a "product life-cycle" component. I use the following approximation:

$$\Delta S_{k,t} = \underbrace{\Delta S_{k,t}^{old,survive} - \overline{S}_{k,t-1}^{old,exit}}_{product\ life-cycle} + \underbrace{n_{k,t}^{new} \times \overline{s}_{k,t}^{new}}_{new\ products} \tag{3}$$

where $\Delta S_{k,t}$ is the firm's annual growth rate, and where the "product life-cycle" component is further decomposed in the annual growth rate of the aggregate sales of products that survived between year $t-1$ and year t, $\Delta S_{k,t}^{old,survive}$, from which I subtract the share of sales that the products that exited between year $t-1$ and t represented in the sales of the firm in year $t-1$, $\overline{S}_{k,t-1}^{old,exit}$. The "new products" component is the product of the rate of introduction of new products in the firm's portfolio $n_{k,t}^{new}$ and the relative sales of new products compared to older products $\overline{s}_{k,t}^{new}$, obtained by taking the ratio of the average sales of a new product in year t to the average sales of a surviving product in year t. I show in Figure 3 that domestic firms grow

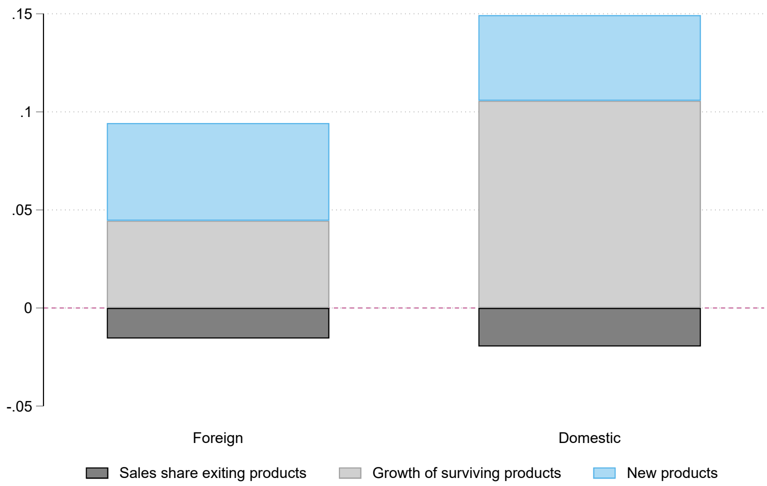

Figure 3: The extensive customer margin is key to firm growth

Notes: Figure represents the average firm-level year-to-year growth components, separated out by the origin of the firms. The sales of exiting products is the average share of sales that the product that exited between the previous year and the current year represented in the previous year. The growth of surviving products is the average growth rate of the total sales of products that survived between the previous year and the current year. The new products components is the product of the average rate of introduction of new products and the average sales of new products compared to older products.

more than foreign firms. This may not seem surprising given that on average domestic firms are smaller than foreign firms. However, this finding is robust to binning firms into categories based on size as determined by sales. In Appendix Figure A.2, I show the comparison of domestic firms and foreign firms in the top quarter of the firm size distribution and in the bottom quarter of the firm size distribution.

For foreign firms, growth appears to be driven equally by the introduction of new products and the growth of surviving goods. The "new products" component is comparable across foreign and domestic firms. The difference in average growth between foreign firms and domestic firms is almost entirely driven by the higher growth rate of surviving products for the latter. Appendix Figure A.3 shows the relative components, illustrating this point even more clearly.

This may be surprising given the fact underlined in Table 2 that domestic firms have a higher rate of introduction of new goods, an element of the "new products" components illustrated in Equation (3). However, I also show in that table that this is driven mostly by very small firms who only sell one product and mechanically appear to sell 100% of new products in the year when they change their product.

Overall, I find that surviving goods contribute a lot to the growth of firms from year to year. This is quite different from what Argente et al. (2019) observe: they find that goods that survive sell less overall from one year to the next, therefore contributing negatively to firm growth. There are two possible sources for this difference. One is that the life-cycle of products is different in Mexico. The second one is that because firms are newer on average in the Kantar data are newer than in the Nielsen data exploited by Argente et al. (2019), the stock of surviving goods are also newer in the Kantar data, and therefore in any year there are fewer very old goods whose sales decrease dramatically in the following year. This hypothesis is partly confirmed by looking at the data separately depending on whether firms are four years or older, or younger than three years (based on the earliest day I observe the firm in the data). In Appendix Figure A.4, surviving goods contribute negatively to the growth of foreign firms which are four years or older. However, it is still not the case for domestic firms that are four years or older. For firms that are less than four years old, the pattern is very similar to the one shown above. This confirms the hypothesis that product life-cycles are different from Mexican firms in Mexico than for US firms in the US, although they may not be different for US firms operating in Mexico, as I will show below.

Another question of interest is how this decomposition varies depending on the time horizon chosen to look at the evolution of sales. Because many products survive only a few years, when looking at the decomposition of the two-year or five-year growth rates, a much higher share of growth comes from new products, both for foreign and for domestic firms. Further, exiting products take a much larger toll on growth, as shown in Appendix Figure A.5. However, the difference is still striking between foreign and domestic firms: even over five years, sales growth for domestic firm comes relatively more from the growth of sales of surviving products than new products compared to foreign firms.

5.2 Domestic products have a slower life-cycle

I again follow Argente et al. (2019) and analyze the evolution of product-level sales over time. I estimate the following equation:

$$\log y_{i,t} = \alpha + \sum_{a=1}^{14} \beta_a D_a + \lambda_{jt} + \theta_c + \epsilon_{i,t} \tag{4}$$

where i is a barcode observed in a certain quarter t, a is a potential age of the good in quarters (between 0 and 14, the mean age attained by products born between 2011Q1 and 2012Q2 and the maximum age reached by products born in 2012Q2 in the dataset). j is a product category and c is a cohort-quarter. I regress a good u's log sales in a quarter t on dummies for the age of this product, product category interacted with quarter fixed effects, and cohort fixed effects (corrected following Deaton (1997)'s suggestion to avoid collinearity). I restrict the analysis to products born between 2011Q1 and 2012Q2, as the mean duration of a product is 14 quarters, which is the period that can be observed with products born in 2012Q2 until 2015Q4. I only keep products which sold a positive amount in each quarter of their "life". I perform this regression separately for domestic and foreign products.

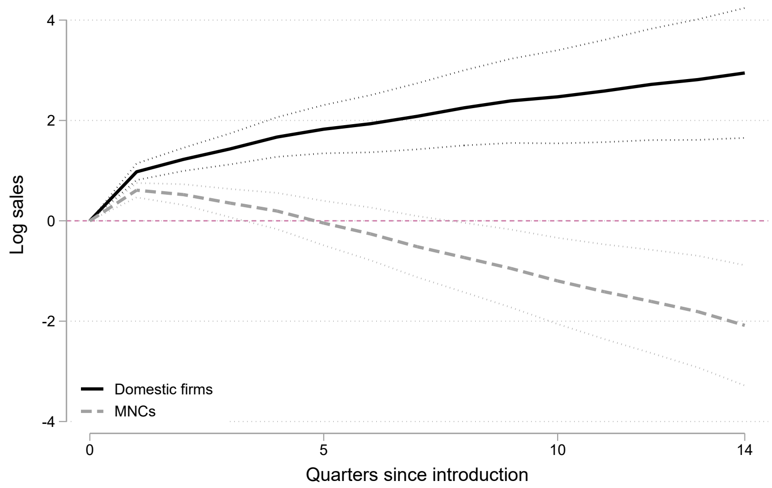

Figure 4: Product life-cycle

Notes: Figure represents the coefficients obtained on the dummies for the age of the product in quarters from a product-quarter level regression where I regress these dummies, quarter by product category fixed effects, and cohort fixed effects on the sales of a product in a given quarter. I run two separate regressions for domestic and foreign products, respectively. 95% confidence intervals are represented by the lighter lines.

In Figure 4, I plot the coefficients obtained on each of the 14 quarter-age dummies. The coefficients obtained for the products introduced by foreign firms are very similar to the ones obtained by Argente et al. (2019) in the United States scanner data: product are born and sell, they exit immediately or sell more, and then their sales decline for a long time until they exit. The authors attribute this to a constant arrival of products in the market, which means that after a while demand for the aging products is captured by newer products released by the same firm (cannibalization) or other firms' products (business stealing). By contrast, when domestic firms introduce new products, sales increase in the initial quarters and then remain high for a long period. While this may seem like an advantage for domestic products, they sell much less at any age, so overall the lifetime total sales of the average domestic product are much lower than the lifetime total sales of the average foreign product. Moreover for a given level of total lifetime sales, displacing sales later in time means that the present discounted values of domestic products is smaller.

A potential explanation for this phenomenon could be the endogenous timing of product of retirement: if foreign firms decide to retire products later than domestic firms conditional on a sales trajectory, I would observe that conditional on surviving a set number of quarters, foreign average product sales decrease over time. Since the product duration is the same between foreign and domestic goods (14 quarters on average, 15 quarters median) it seems unlikely. I can further rule out this hypothesis by showing that the survival rate of foreign products is not different from that one of domestic products as they age, as shown in Appendix Figure A.6.

A potential concern is again that the difference between domestic firms and foreign firms be entirely driven by the difference in sizes. The findings are robust to controlling for firm size as measured by firm sales, as shown in Appendix Table B.4, Columns (3) and (4). When looking separately at four categories of firms, binned based on their sales, the difference between foreign and domestic firms only holds for the first two bins. Firms on the larger side of the spectrum do not exhibit this difference. In Appendix Figure A.7, I show similar figures as above for firms in the bottom 25% and the top 25% of the size distribution. This means that the average difference we observe is driven by differences between small domestic firms and small foreign firms. This is significant: it means that large Mexican firms overcome the problem we later describe in detail. By contrast, foreign firms never face this problem, regardless of their size. Even if they are very small, consumers trust their new products to be of high quality. This suggests that some Mexican firms have the potential to grow and be as productive as MNCs operating in Mexico. However, only some of them are able to overcome the trust issue. It may be the case that the selection on the ability to gain consumers' trust is not efficient, and that some firms who have the potential to be very productive do not grow.

Because of the particular necessities of this regression, it is difficult to slice the data further between firms that are older and firms that are younger: 95% most of the products first appearing in the data between 2011Q1 and 2012Q2 and surviving 14 quarters were introduced by firms born in 2010. The results do not appear to be driven by younger firms.

5.3 The extensive customer margin is key to firm growth

I now decompose firm sales in a different manner. Here, I follow Einav et al. (2021) in studying the exact decomposition of a firm's sales:

$$\text{Sales} \equiv \text{Customers} \times \frac{\text{Quantity}}{\text{Customers}} \times \underbrace{\frac{\text{Sales}}{\text{Quantity}}}_{\text{Unit value}}$$

This equation can be interpreted in the following way: in order to double sales, firms may do one of three things, *ceteris paribus*

(i) double their number of customers - the extensive margin

(ii) double the number of items they sell to each customer - one intensive margin

(iii) double the monetary value obtained from each unit sold - another intensive margin

The firm upgrading literature, and particularly the technology adoption literature, has mostly focused on (iii). The intuitive argument is that if a firm increases the quality of its output, it will be able to sell each unit for a higher price, and probably attract more demand. Here, I remain agnostic and look at which margin seems to generate the most variation in sales. Of course, these three variables are endogenous as highlighted by the sentence above and I am not making any causal claim. I begin by taking logs of each element:

$$\log(\text{Sales}) = \log(\text{Customers}) + \log(\text{Quantity per Customer}) + \log(\text{Unit value})$$

I perform three regressions, regressing each element in turn on the log of Sales.

$$\log\left(\text{Customers}_{kt}\right) = \alpha + \beta_C \log\left(\text{Sales}\right)_{kt} + \eta_k + \vartheta_t + \epsilon_{kt} \tag{5a}$$
$$\log\left(\text{Quantity per Customer}_{kt}\right) = \alpha + \beta_Q \log\left(\text{Sales}\right)_{kt} + \eta_k + \vartheta_t + \epsilon_{kt} \tag{5b}$$
$$\log\left(\text{Unit value}_{kt}\right) = \alpha + \beta_U \log\left(\text{Sales}\right)_{kt} + \eta_k + \vartheta_t + \epsilon_{kt} \tag{5c}$$

where i is a firm and t is a year. I control for firm fixed effects (η_k) and year fixed effects (ϑ_t) which means the coefficients are identified from looking at the years when firms grew faster, or slower, than their own average. By construction,

$$\beta_C + \beta_Q + \beta_U \equiv 1$$

The results are presented in Figure 5. The customer margin accounts for 60% of sales variation

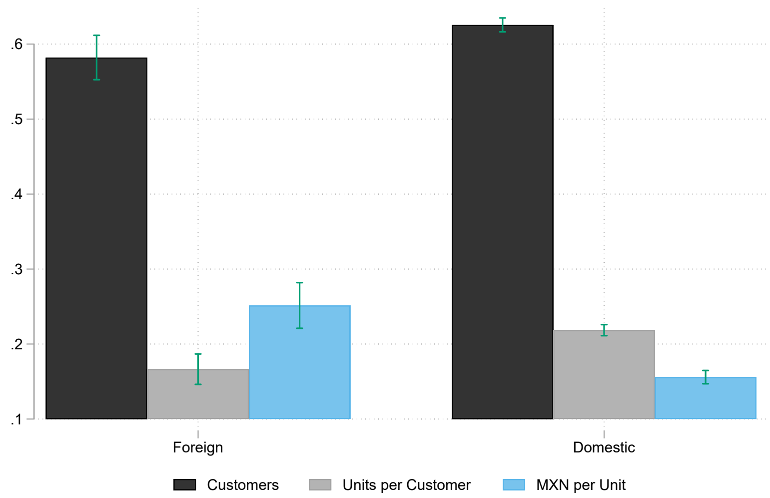

Figure 5: The extensive customer margin is by far the most important

Notes: Figure represents the coefficients obtained on log sales from firm-year-level regressions of log sales, product category and year fixed effects on log customers, log units per customer and log monetary value per unit. I run each of the three regressions separately for foreign and domestic firms. 95% confidence intervals are represented using the bars. Table B.5 shows the numerical values of these coefficients and an alternative specification.

within firms over time. This is true for both domestic and foreign firms, it appears that for domestic firms, the customer margin seems slightly more important, while the value margin seems relatively less important than for foreign firms. Relating this finding to the last fact about the product life-cycle, I interpret the rapid decay of sales of products introduced by foreign firms as they age as customers being attracted to new products in the initial quarters of the life of a product, and customers being increasingly attracted away from these products and towards newer products from the same firm, or other or newer products from other firms. By contrast, the sustained sales of domestic products even after two years could suggest that even if early customers grow tired of these products and stop buying them, more customers arrive to replace them as the products age.

This fact may vary a lot by industry. Because the regressions control for firm fixed effects, effectively comparing years in which firms grow faster than their own average, I am not excessively worried about industry variation. Nevertheless, I study this by taking the analysis to the firm-product category level. Appendix Figure A.8 shows that across the top 20 categories, the customer margin is the most important one in 19 categories, the only exception being perfume for which it makes sense that the price obtained per purchase would matter a lot. This finding confirms that this analysis is capturing an important dimension of how the firms I am studying grow.

This fact is less amenable to concerns about firm size, partly because here the point is not that there is not a large difference between domestic and foreign firms here. Nevertheless, we show in Appendix Figure A.9 that the result is robust when looking only at firms in the top quarter of the firm size distribution or only at firms in the bottom quarter of the firm size distribution. The results are also robust to firm age heterogeneity (not shown).

5.4 The intensive customer per product margin is key to customer growth

Because the extensive customer margin appears to be so important according to the previous analysis, I turn to study the question of how to acquire more customers. To double their number of customers, firms may firms may do one of three things, *ceteris paribus*

(i) double the number of markets they operate in - the extensive margin

(ii) double the number of customers they reach in each market - the intensive margin

Markets can be understood in several different ways: in terms of geography, distribution channels, or product. The firm upgrading literature has mostly focused on the extensive margin. The intuition behind is that firms face a barrier in accessing new markets, such as exports (Atkin et al. (2017a)) or large, tender-based markets (Hjort et al. (2020)). A few recent papers have shown that access to better inputs through trade with high-income countries leads the most performing firms to expand their product scope (**?**, **?**). Intuitively, it means that if there are customers who do not like the current products that the firm has in its portfolio, but may like slightly different products, the firm may increase sales by iterating on its current varieties. Product scope expansion might be easier for firms than quality upgrading which often means adopting new technologies or techniques. However, product scope expansion still imposes some fixed cost on the firm. I look at the following exact decomposition:

$$\text{Customers } \equiv \text{Products} \times \frac{\text{Customers}}{\text{Products}}$$

which yields, taking logs

$$\log(\text{Customers}) = \log(\text{Products}) + \log(\text{Customers per product})$$

I perform two regressions, regressing each element in turn on the log of the number of customers:

$$\log(\text{Products})_{kt} = \alpha + \beta_M \log(\text{Customers})_{kt} + \eta_k + \vartheta_t + \epsilon_{kt} \tag{6a}$$

$$\log(\text{Customers per product})_{kt} = \alpha + \beta_C \log(\text{Customers})_{kt} + \eta_k + \vartheta_t + \epsilon_{kt} \tag{6b}$$

where η_k are firm fixed effects and ϑ_t are year fixed effects. By construction

$$\beta_M + \beta_C \equiv 1$$

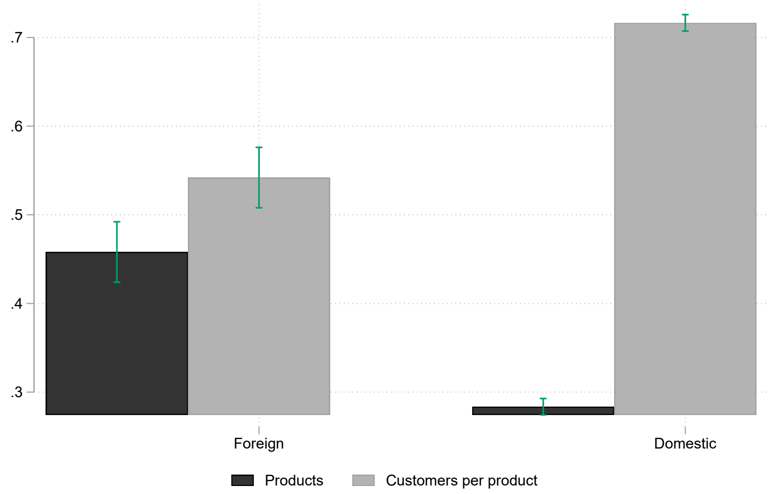

Figure 6: The intensive customer per product margin matters more for domestic firms

Notes: Figure represents the coefficients obtained on log customers from firm-year-level regressions of log customers, product category and year fixed effects on log products and log customers per product. I run each regression separately for foreign and domestic firms. 95% confidence intervals are represented using the bars.

Figure 6 shows the coefficients obtained for domestic and foreign firms. For the latter, the two margins do not appear to be extremely different. By contrast, for domestic firms the intensive margin accounts for over 70% of the variation in the number of customers, while the extensive margin accounts for less than 30%. This suggests that it is easier for domestic firms to grow by convincing more customers to buy their existing products, than to grow by adding additional products to their portfolio. This is coherent with the first two facts showing that for domestic firms, the growth of the sales of surviving goods is a strong determinant of firm-level sales growth, and that the products introduced by domestic firms acquire customers over time. Moreover, I showed in Section 3 that when I exclude small domestic firms that only carry one good, domestic firms have a lower rate of introduction of new products than foreign firms on average. This may be a strategic response to the difficulty they face in introducing new products.

A potential concern here is that the difference between domestic firms and foreign firms be entirely driven by the difference in sizes. We cannot control for firm size in the above regressions as we are controlling for firm fixed effects. The concern would then translate into thinking that when a firm is already large and has many customers, faster growth over time cannot be achieved by selling a product to more consumers faster, but by releasing more products faster, while when a firm is small and has few customers (result obtained for domestic firms), it is possible to accelerate customer acquisition. When looking separately at four categories of firms, binned based on their sales, the difference between foreign and domestic firms hold out qualitatively for all bins, alleviating this concern. In Appendix Figure A.10, I show similar figures as above for firms in the bottom 25% and the top 25% of the size distribution. The results are also robust to firm age heterogeneity (not shown).

5.5 The new customers of older domestic products are poorer

The last fact sheds light on the characteristics of the new customers acquired by products as they age. I estimate the following equation:

$$\log y_{i,u,t} = \alpha + \sum_{a=1} \beta_a D_a + \lambda_{jt} + \theta_c + \delta_g + u_{i,u,t} \tag{7}$$

where i is a good observed in a certain quarter t, u is the individual who purchased it, a is a potential age of the good in quarters (between 0 and 14, the mean age attained by products born between 2011Q1 and 2012Q2 and the maximum age reached by products born in 2012Q2 in the dataset). j is a product category and c is a cohort-quarter. I regress the annual expenditure of new customers u of good i's in quarter t on dummies for the age of this product, product category interacted with quarter fixed effects, and cohort fixed effects (corrected following Deaton (1997)'s suggestion to avoid collinearity). I restrict the analysis to products born between 2011Q1 and 2012Q2, as the mean duration of a product is 14 quarters, which is the period that can be observed with products born in 2012Q2 (they are effectively 14 quarters old in 2015Q4). I perform this regression separately for domestic and foreign products. I control for city fixed effects δ_g based on where customer u lives.

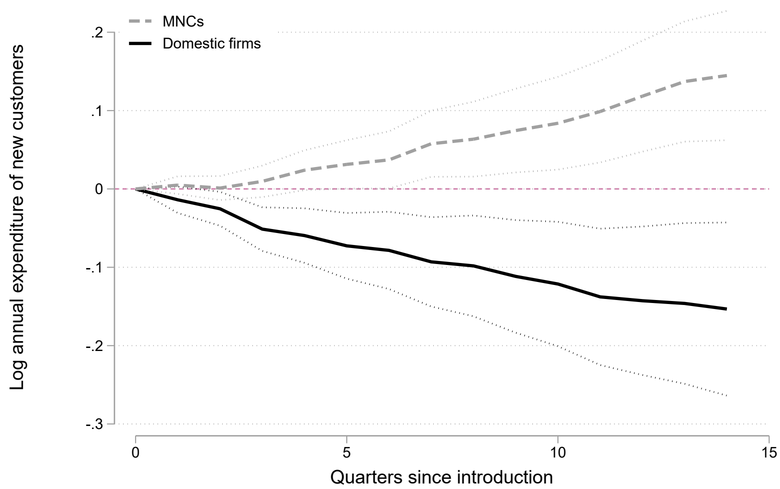

Figure 7: The new customers of older domestic products are poorer

Notes: Figure represents the coefficients obtained on the dummies for the age of the product in quarters from an individual-product-quarter level regression described in Equation (7) where I regress these dummies, quarter by product category fixed effects, cohort fixed effects and city fixed-effects on the average annual expenditure of the new customers of a product in a given quarter. I run two separate regressions for domestic and foreign products, respectively. 95% confidence intervals are represented by the lighter lines. Table B.7 shows the numerical values.

Figure 7 shows the coefficients obtained on each of the 14 quarter-age dummies. The new customers who start buying a foreign product as it ages are richer than the customers who started buying the foreign product in the very first quarters of its existence. By contrast, the new customers who start buying a domestic product as it ages are significantly poorer than the customers who started consuming the same product in its initial quarters of existence. This fact suggests that the process by which domestic firms acquire demand is very different from the one foreign firms go through. This is confirmed by an alternative description of consumers: in Figure A.11, we show the results of a similar regression where the outcome is the average socio-economic status of new customers, measured on a scale from 1 to 6. We find that customers who buy older foreign products hail from a higher socio-economic status that customers who buy new foreign products, while this is not true for domestic products.

A potential concern is again that the difference between domestic firms and foreign firms be entirely driven by the difference in sizes. The findings are robust to controlling for firm size as measured by firm sales, as shown in Appendix Table B.7, Columns (3) and (4). Binning firms into four different categories based on their sales does not work here. This is because the products released by large firms typically acquire a lot of consumers within the first few months and then do not acquire many new customers, making the regression impossible to estimate just for very large firms. Similarly the products released by very small firms get few customers in total, so the regression is poorly estimated.[18] The results are robust to firm age heterogeneity (not shown).

One may think that there is a supply-side explanation to this pattern. For example, if domestic products are distributed through certain stores and foreign products are distributed through other stores, it may be that there the distribution dynamics specific to each type of firm account for the divergence the new customers profile over time. Specifically, if domestic products are better able to go to more remote, and poorer areas, then the new customers they are getting are not arriving later because of learning but because the products were not available to them before. I am not too concerned about this because the regression includes city fixed effects, which suggests that this finding holds within cities.

I pursue this concern by asking whether the new cities that are reached by products as they age are different depending on whether the product is sold by a domestic firm (I would expect the cities to be increasingly small and rural) or by a foreign firm (I would expect the products to only diffuse to big cities). To answer this question, I implement a similar estimation equation as shown in Equation (7) but at the barcode-city-quarter level, where I only keep the new cities where the barcode makes sales in each quarter after it is born. The results are shown in Appendix Table B.8. I find that the new cities that products reach when they are older are smaller in population (Columns (1) and (2)) and less dense (Columns (3) and (4)) than the cities reached when the products are new. However, this trend is common to both domestic and foreign goods. I find that the new cities that domestic product reach when they are older are further away from Mexico City, the capital, than the cities by the same products when they were new. This trend does not exist for foreign products: in fact, it appears to be almost the opposite. However, the coefficients for both set of products are very noisy, so it does not appear to be a solid threat to out interpretation of fact # 5.

[18] The results are robust to estimating the regressions just for firms in the second to last quarter of the firm size distribution, or just for firms in the second quarter of the firm size distribution, but it does not appear interesting enough to be shown in the appendix.

6 Model

In this section I introduce a conceptual framework in which I highlight the hypothesis that uncertainty about product quality generates these facts.

6.1 Setup

In this model, agents are consumers faced with a new good of unknown quality x. x is a random variable from a known distribution with prior mean μ_0. Agents choose whether to purchase the good or not, maximizing

$$u(\mu) = \max\{\mu - \beta_i p, 0\}$$

where β_i represents price-sensitivity. For simplicity, I suppose there are only two possible types of agents: $\beta_i \in \{\beta_L, \beta_H\}$ where $\beta_H > \beta_L$. There is a higher share of the market who is of the second type $\gamma_H = 1 - \gamma_L$. This game is dynamic. In each period, agents decide whether to purchase the good or not. If they purchase the good, they immediately learn the true quality x. They can then use this information to decide whether they will purchase the good in the next period. I call this learning through individual experimentation "individual learning". Agents buy at most three times in a row (three times if they like the good, one time if they don't). Agents may also learn through observation: by looking at whether people who have tried the good continue to purchase it or not, they can update their belief about the quality of the good. I call this "observational learning".

6.2 Individual learning

Suppose that a period t no agent has purchased the good yet. Everyone has the same prior μ_t. Each agent decides whether

$$\mu_t - \beta_i p \lesseqgtr 0$$

If one agent decides to purchase the good and not the other, it must mean that it is the agent with the lesser price-sensitivity β_L. She immediately learns the true quality x. However, the other agents don't learn anything from observing this initial purchase. $\mu_{t+1} = \mu_t$.

6.3 Observational learning

In the following period $t + 1$, the leader assesses whether

$$x - \beta_L p \lesseqgtr 0$$

Upon observing this decision, the other agents learn whether

$$x \lesseqgtr \beta_L p$$

and can update their belief accordingly:

$$\mu_{t+2} = \begin{cases} < \mu_{t+1} & \text{if } x < \beta_L p \\ \geq \mu_{t+1} & \text{if } x \geq \beta_L p \end{cases}$$

Importantly, this is anonymous: consumers do not need to know who has purchased the good, only that the good has been purchased several times, as an agent who has decided against purchasing the good in the initial period rationally expects that people who have decided to try are less price-sensitive than himself.

6.4 Sales trajectories

This model generates the following sales trajectory for a "successful" product $x > \beta_H p$, when $\mu_0 < x$ ("uncertainty") and for when $\mu = x$ ("no uncertainty"), where each point represents the fixed effects of the product aging one quarter on its sales compared to the initial quarter. Figure 8 strongly resembles Figure 4 which plots the coefficient on the dummies for the age in

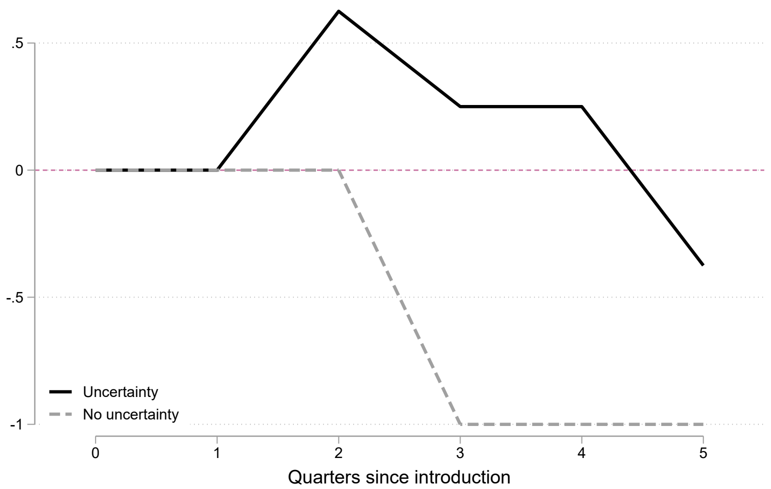

Figure 8: Sales trajectories of a successful product given uncertainty

Notes: Figure represents the simulated coefficient on the dummies for age of the product in quarters one would get by running a product-quarter level regression of these dummies on sales of a successful product in the model.

quarters of the products in the data.

7 Mechanisms

In this section, I document the mechanisms described in the model. First, I show that the different patterns we are observing between foreign and domestic products is not entirely driven by unobserved quality differences, as evidenced by consumers' repeat purchase patterns, but by a differential gap between perceived and experienced quality between domestic and foreign products. Second, I show evidence that there is uncertainty at play, as consumers increase the quantity they purchase conditional on purchasing again.

7.1 An information gap

Goods that are imported from high-income countries are often thought to be of a higher quality. A large literature has shown that this is true on average (Hummels and Klenow (2005), Schott (2004)). Part of the differential patterns I describe in this paper could therefore be attributed to unobserved (to the econometrician) quality differences between foreign and domestic products, even conditional on price. I therefore propose to follow Ackerberg (2001) by studying consumers' repeat behavior. The intuition is that most of the goods observed in the data are experience goods, therefore once the consumer has tried it once, they know the quality of the good and will no longer be influenced by external signals about quality (advertising in Ackerberg's case). I therefore transform the data into a consumer-year-barcode matrix, and conserving only the products that are available to consumers from one year to the next, I look at the probability of buying a good in a given year depending on whether the consumer has purchased the good the year before. I estimate the following equation:

$$y_{ikt} = \alpha + \beta y_{ik,t-1} + \gamma D_k + \delta D_k \times y_{ik,t-1} + d_k + \delta_t + \xi_i + \epsilon_{ikt} \tag{8}$$

where i is the consumer, k is the barcode, and t is the year. The parameter of interest is β, which measures the effect of the consumer's individual experience with the good k at $t-1$, $y_{ik,t-1}$ on subsequent consumption (at t) of the barcode. The second parameter of interest is the interaction coefficient δ, which measures the differential impact of experience with a brand for a domestic brand compared to a foreign brand.

I cannot claim that experience with a good in year $t-1$ is exogenous, as individuals' exposure to a product, both in terms of advertising and choice sets, may be strategically chosen by forward-looking firms in year $t-1$ by firms who anticipate consumers' propensity to consume in year t. However, I can control for individual fixed effects ξ_i, and so I am arguably measuring the average influence of past product exposure on current consumption choices, controlling for individual preferences, advertising exposure and choice sets. In my preferred specification, I also control for barcode fixed effects d_k, which suggests that I also measure the average effect of past product exposure controlling for the product's specific strategy to reach consumers in year $t-1$.

The results are described in Table 3. In Column (1) I find that previous experience with a barcode is predicted to raise the probability of consumption of that barcode in the following year by 0.42, *ceteris paribus*, a very high effect compared to the control mean of less than 1%. Although a domestic good is less likely to be consumer if the consumer has not tried it before, conditional on being consumer it is more likely to be consumed again, an effect if 0.036, almost 10% of the size effect of the previous consumption for all goods. This is a key result, as it shows that although consumers might be reluctant to buy domestic goods in general, once they have tried it they are more likely to buy it again than once they have tried a foreign good. It suggests that the differential between the revealed quality and the perception of quality is higher for domestic goods, an information gap that is much stronger for domestic goods.

One may worry that the coefficient we find is not due to a gap in information, but to systematic differential exposure of consumers to domestic products in the first place. If this is the case, then the interaction coefficient would be upward biased. In Column (2) I include product fixed effects, which partially take care of this. I find that the repeat coefficient is lower, although still very high at 0.33, suggesting that overall the repeat behavior might be less systematic if all products had the same chance to expose consumers. However the interaction coefficient with the dummy for domestic goods is higher at 0.045, well above 10% of the effect of previous consumption, strengthening the argument for an information gap for domestic products instead of (only) a quality gap.

A question is therefore what can domestic firms do in order to stimulate the purchase of their new products, which we have shown struggle more to sell than the new products of foreign firms? I propose to look at how the probability of consuming a new barcode is influenced by the previous consumption of a brand. Equation 8 is therefore modified in order to cover only products that the consumer has not purchased before, and regress the probability of consuming them on a dummy for whether the consumer has consumed any other product from that brand (excluding the barcode itself) in the previous year. Column (3) shows that having consumed a brand is predicted to raise the probability of consumption of a barcode non previously consumed by 1 percentage point, *ceteris paribus*, a huge effect compared to the baseline probability of 0.4%. This suggests that consumers are inferring from their previous exposure to brands that they might like other products from that brand. The first coefficient shows that consumers are less likely to buy a new domestic good than a new foreign good, which is not surprising given the result in Column (1). However, the last coefficient in Column (3) shows that having experience with a domestic brand has a 50% larger effect on the probability to consume an unknown barcode from that brand, than experience with a foreign brand. This effect is confirmed, and larger in proportion, when including product fixed effects in Column (4).

In Columns (5) and (6), I repeat the analysis with experience at the firm level. The effects are smaller but comparable. This makes sense because the name of a firm is less salient to consumers than the name of the brand they purchase goods from, so they learn less from the signal. Similarly, while national reputations matter as underlined by Cagé and Rouzet (2015) and Bai et al. (2019), I expect their signal to be less strong than that of firms or brands[19]. Importantly, the domestic firm experience effect is almost 100% larger than the foreign firm experience effect.

7.2 Consumers are learning

The previous section provides evidence that the gap between consumers' prior about quality before trying the good and their posterior is larger for domestic firms than for foreign firms. One can therefore wonder if consumers are aware of that gap and how they choose their consumption given this. In this section, following Crawford and Shum (2005), I exploit data corresponding to consumers' repeat purchases of products. Contrary to Crawford and Shum (2005) however, I observe the intensive margin of the purchase of consumers: the quantity of goods. If I see that consumers who buy a good for the nth time buy a larger quantity than those buying a good for the n-1th time, it suggests that consumers are using what they learned from their experience

[19] I do not show the results here as 100% of consumers have tried at least one barcode from Mexico so I cannot estimate the interaction coefficient on country of origin and Domestic. Results are available upon request.

	Current consumption					
	All barcodes		Not previously consumed barcodes			
	(1)	(2)	(3)	(4)	(5)	(6)
Domestic	-0.002	0.000	-0.001	0.000	-0.001	0.000
	(0.000)	(.)	(0.000)	(.)	(0.000)	(.)
Previous consumption of barcode	0.416	0.329				
	(0.000)	(0.000)				
Previous consumption of barcode X Domestic	0.036	0.045				
	(0.000)	(0.000)				
Previous consumption of brand			0.012	0.009		
			(0.000)	(0.000)		
Previous consumption of brand X Domestic			0.005	0.006		
			(0.000)	(0.000)		
Previous consumption of firm					0.007	0.005
					(0.000)	(0.000)
Previous consumption of firm X Domestic					0.006	0.006
					(0.000)	(0.000)
Hhd FEs	Yes	Yes	Yes	Yes	Yes	Yes
Barcode FEs	No	Yes	No	Yes	No	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Control mean	0.008	0.008	0.004	0.004	0.002	0.002
N hhd	6888	6888	6888	6888	6888	6888
N	178991568	178991568	176952267	176952267	176952267	176952267
R2	0.19	0.24	0.01	0.06	0.01	0.06

Table 4: Evidence of a larger posterior-prior gap for domestic goods

Notes: Table shows the results of a barcode-household-year level regression of a dummy for consumption in the previous year, a dummy that turns on if the product if Mexican, and the interaction of these two dummies, on a dummy that turns on if the individual has consumed the barcode in the current year. In Columns 1 and 2, previous-year consumption is defined as previous consumption of the barcode. In Columns 3 to 6, I only look at current consumption of barcodes that were not consumed by the household in the previous year. Past consumption is defined at the brand level (3 and 4) or firm level (5 and 6), excluding the barcode itself. I always control for household and year fixed effects, while sometimes including barcode fixed effects. Standard errors are reported in parenthesis.

the n-1th time. I estimate the following equation:

$$y_{ikt} = \alpha + \sum_n \beta_n \{N_{ikt} = n\} + \sum_n \delta_n D_k \times \{N_{ikt} = n\} + p_{ikt} + d_k + \delta_t + \xi_i + \epsilon_{ikt} \tag{9}$$

Where again i is the consumer and k the barcode but t is the month. y_{ikt} is the log quantity of the product k purchased by consumer i at time t. I regress this on a series of dummies that represent the order in which the barcode k was purchased by the household. I am interested in the coefficients $\{\beta_n\}_{n=1}^N$ which describe the order in which that particular purchase took place, relative to the barcode and the household who purchased it. It captures the learning effect associated with the repeat purchase of the same product. I interact a dummy D_k that turns on if the product is domestic with the dummies for the order of the purchase. Because of the importance of having a precise estimation of the order in which households purchased the goods, I only keep new products in this estimation, where new products are defined as described in Section 3.2. I control for the price paid by consumer i for product k at period t. Last, I include household fixed effects ξ_i, month fixed effects δ_t and barcode fixed effects d_k.

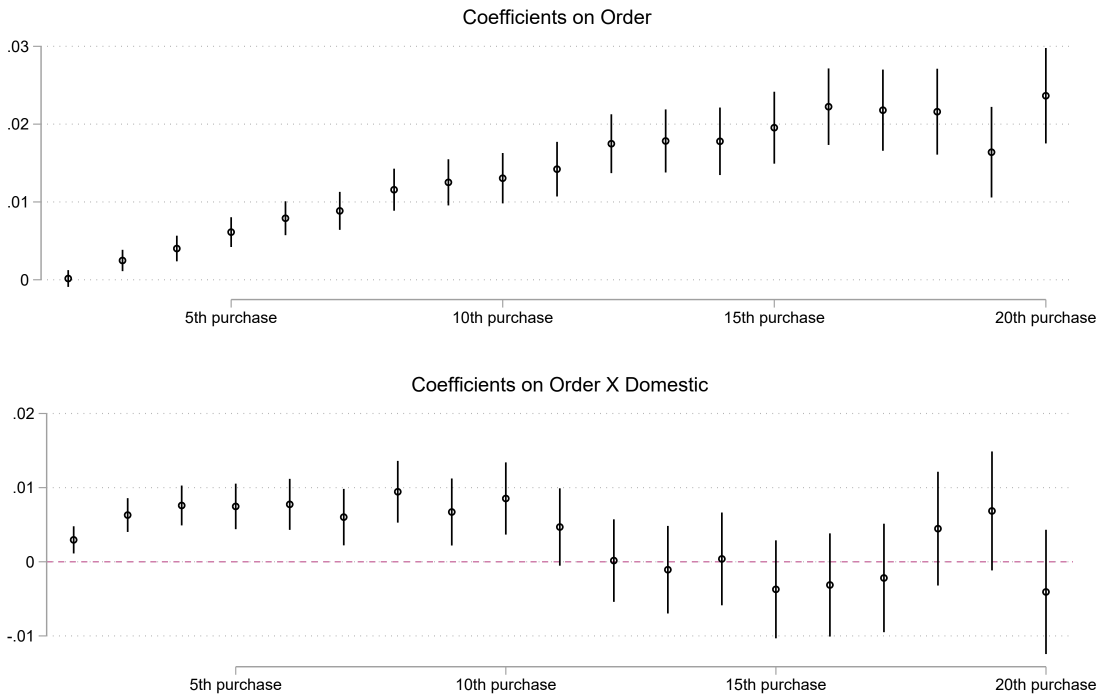

Figure 9: Evidence of learning behavior

Notes: Figures shows the results of a purchase-household level regression, for barcodes purchased up to 20 times, of the quantity of the barcode chosen during the purchase, on dummies describing the order in which the barcode was purchased by the household (coefficients shown in the top panel) and on dummies interacting the order and the fact that the good is produced by a domestic firms (coefficients shown in the bottom panel). I always control for household fixed effects, barcode fixed effects and year fixed effects. Standard errors are reported in parenthesis.

Figure 9 shows the results estimated for up to twenty purchases of the same barcode. The first panel of the figure shows that for all barcodes, being purchased for the 10th time by the same household is predicted to raise the quantity purchased by 1.5 to 2%. This effect is small but statistically significant, and must be assessed against the fact that 75% of purchases have 1 as a quantity. This suggests that there is some learning going on. Importantly, the coefficients stagnate starting at the 12th purchase, which also makes sense given that there is a limited amount of information that any household might be able to learn about a particular good. The bottom panel sows the coefficients obtained on the interaction of the order of the purchase and the dummy representing whether the goods are produced by a domestic firm. The first 11 coefficients are positive, statistically significant and economically important as their size is comparable to the size of the coefficients on the order (up to 1 percentage point additional for the 6t purchase for example). This suggests that there is more learning going on for domestic goods, as consumers change their behavior more as they repeat their purchase of a domestic good than when they repeat the purchase of a foreign good.

One can ask whether these patterns hold for the size of barcodes purchases, within products: if consumers are uncertain about the ability of a certain brand to deliver high-quality milk for example, they might start by buying a small bottle of milk, and only if they are satisfied and buy it again will they buy a bottle of a larger quantity. This is indeed the cases and is confirmed in Appendix Figure A.13, where I present this analysis based on three different definitions of goods. It is more difficult to identify new products following the method described in Section 3.2 when using larger product definitions, which may make the analysis less precise. In particular for Figure A.13c there are few brand-category new products, especially Foreign ones.[20] This may explain why we find a negative effect of the order on foreign products. However, the effect of the order on domestic product is still positive and significant.

7.3 Importance of quality certainty

The previous subsection suggests that there is some consumer learning. However, many forms of learning are possible: learning about how to use products from a certain brand for example, or learning through social exposure that the product is socially valuable. In the model, learning comes from uncertainty about product quality. I therefore turn to showing that quality matters.

The importance of quality may affect how people learn about product quality. For example, if food products are of low quality, it may imply that household members get sick. On the contrary, if paper products are of low quality, it has less dramatic implications. Therefore, our model implies that consumers would take more precaution in buying new food products than in buying new paper products. Further, they would learn more from consuming good brands of food products than from consuming good brands of paper products.

I test this by estimating the following equation:

$$y_{u,ik,t} = \alpha + \beta y_{uk,t-1} + \gamma D_i + \delta D_i \times y_{uk,t-1} + \xi_u + \epsilon_{u,i,t} \tag{10}$$

which is similar to Equation 8: $y_{u,ik,t}$ is current consumption of product i (brand k) by household u and time t, $y_{uk,t-1}$ is previous consumption by household u of brand k excluding barcode i, but importantly the dummy D_i represents whether the quality of that product is salient or not.

[20]There are about 700 "new" foreign products in this category as opposed to 2,000 "new" domestic products.

I start by comparing food to non-food products. Column (1) of Table 4 shows the results. Previous exposure to a brand is predicted to increase the consumption of any product by 0.017 *ceteris paribus*, similar to what I showed in Table 3. This effect increases by 0.005 or almost a third when the product is a food product as opposed to a non-food product, confirming that when quality is more important, consumers learn more from the brands they consume.

	Current consumption		
	All	Milk	Pads
	(1)	(2)	(3)
Previous consumption	0.018	0.021	0.012
	(0.000)	(0.000)	(0.000)
Salient category	0.002	-0.005	-0.005
	(0.000)	(0.000)	(0.000)
Previous consumption X Salient	0.005	0.010	0.005
	(0.000)	(0.000)	(0.000)
Hhd FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
Control mean	0.009	0.009	0.009
N hhd	11966	11966	11966
N	448683433	15059005	15365529
R2	0.01	0.01	0.01

Table 5: Learning by quality salience

Notes: Table shows the household-barcode-year-level regression of a dummy indicating whether the household has consumed products for a similar brand in the previous year, whether the product belongs to a category for which quality is salient, and an interaction of these two dummies, on a dummy indicating whether the household has consumed the barcode in the observation year. In the first column, I look at all products and the salient category is food. In the second column, I keep only milk-products and the salient category is infant formula. In the third category, I keep baby diapers and sanitary pads and the salient category is baby diapers. I always control for household and year fixed effects. Standard errors are reported in parenthesis.

However, food and non-food products are different not only with respect to the importance of quality, but also in terms of the structure of demand, which may influence learning. For example, households typically buy food every week or even several times a Iek, while they probably buy toilet paper once a month or even less frequently. This would make learning slower for the latter products, regardless of the importance of quality. Moreover, food and non-food products are different in terms of supply chains and marketing strategies, which may influence learning as Ill. So finding different learning speeds between food and non-food products might be attributable to these factors and not to quality salience.

Therefore, I exploit the heterogeneity of quality salience among more narrow product categories. Most people would agree that the safety of food being fed to babies and young children is relatively more important than the safety of other foods. In Column 2, I therefore compare the effect of brand exposure on the probability of buying an infant formula products to the effect of brand exposure on the probability of buying another milk product. I find that the effect of exposure to the brand is much larger for infant formula products: it increases the probability of buying a product from the same brand by 0.041, an effect that is twice larger than the standalone "other-products" brand effect at 0.025. Similarly, in Column (3) I compare the effect of brand exposure on the probability of buying baby diapers to the effect of brand exposure on the probability of buying adult sanitary pads. I again find that the brand effect is larger for baby products. This analysis therefore suggests that quality matters in the way consumers learn about previous experience when choosing goods they have not consumed before.

7.4 Price sensitivity

In the previous two subsections, I show that consumers seem to be learning, or updating their beliefs about goods they previously did not consume, from the signals generated by consuming from brands. They seem to be learning relatively more from consuming Mexican brands, suggesting that these brands have *ex ante* lower or noisier priors. I further show that they seem to be learning relatively more for products for which quality is more salient, confirming our hypothesis that concerns about quality drive this learning process. I now turn to the last element of our hypothesis: that income is a binding constraint in choosing to experiment with unknown goods. I propose to estimate the following equation:

$$y_{u,ik,t} = \alpha + \beta y_{uk,t-1} + \gamma D_u + \delta D_u \times y_{uk,t-1} + \mu_i + \epsilon_{u,i,t} \tag{11}$$

Which again estimates the impact of $y_{uk,t-1}$, previous consumption of brand k, on $y_{u,ik,t}$, the current consumption of product i (brand k) by household i and time t, but importantly the dummy D_u represents whether the households' expenditure in year $t-1$ puts them in the bottom quarter of the expenditure distribution in the sample in the year t(which I will henceforth call the "low-expenditure" group. I cannot control for household fixed effects in this context, and therefore control for barcode fixed effects μ_i instead.

Table 5 shows the results of the estimation in the same order as in Table 3. I find that having consumed for a brand is predicted to raise the probability to purchase a previously not-purchased product by a large, positive and significant amount, *ceteris paribus*. This effect is considerably smaller for low-expenditure households. Focusing on Column 1, I find that the effect is a third smaller for low-expenditure households. As a benchmark, I show in Column 2 the effect of having consumed the exact same good, which is again about 15 times larger than the brand effect, is much smaller for low-expenditure households. Last, Columns 3 and 4 show robustness checks looking at larger groups: firm and country, and the results are similar.

Because exposure to brands is not exogenous, one may be concerned that what I am capturing here is simply the fact that richer consumers consume more new varieties, perhaps because firms direct innovation towards them as suggested by Jaravel (2019). Contrary to his finding that households in the top quintile of the income distribution spend up to 8% of their expenditure on new varieties, compared to 6% for households at the bottom quintile of the income distribution, I do not find systematic variation between households along that dimension, as shown in Appendix Figure A.14. Given a similar rate of exposition to new goods, I therefore conclude that the regression results shown above reflect the fact that lower-income households learn less individually about new goods, which supports the model's mechanisms.

	Current consumption			
	Brand	Barcode	Firm	Country
	(1)	(2)	(3)	(4)
Previous consumption	0.024	0.344	0.020	0.014
	(0.000)	(0.000)	(0.000)	(0.000)
Low expenditure	-0.003	-0.007	-0.002	-0.003
	(0.000)	(0.000)	(0.000)	(0.000)
Previous consumption X Low expenditure	-0.008	-0.066	-0.007	-0.003
	(0.000)	(0.000)	(0.000)	(0.000)
Barcode FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Control mean	0.009	0.016	0.006	0.009
N hhd	11966	11966	11966	11966
N	448683433	459375213	448683433	448683433
R2	0.05	0.18	0.05	0.05

Table 6: There is relatively less learning among the poor

Notes: Table shows regression of a dummy for consumption in the previous year, a dummy that turns on if the household is in the bottom quarter of the expenditure distribution, and the interaction of these two dummies, on a dummy that turns on if the individual has consumed the barcode in the current year. In Column 1, previous-year consumption is defined as previous consumption of the brand that the product belongs to, while I only look at current consumption of products that were not consumed before. In Columns 3 and 4 I do the same but for the firm and country that the product belongs to, respectively. Column 2 looks at previous consumption of the product itself and therefore includes all products, whether consumed or not in the current year. I always control for barcode and year fixed effects. Standard errors are reported in parenthesis.

8 Structural Estimation

In a given product category k, for a given market geographical m and time t, define possible products $j \in J_{kmt}$. We may divide this by income group y. We look at the quantity shares of products defined as,

$$s_{jmt}(y) = \frac{q_{jmt}(y)}{q_{Jmt}(y)}$$

where q_{jmt} is the quantity consumed on the product and q_{Jmt} is the quantity consumed on the product category as a whole, in the market mt. We write it this way because J represents all the possible products one could choose from that product category. Define j^0_{km} the product which has the largest quantity within J_{km0}, the set of domestic products available at the beginning of times in market m. The rest of the analysis will be in relation to this product.

$$\ln s^k_{jmt}(y) - \ln s^k_{j^0_{mk}mt}(y) = -\alpha(y)(p_{jt} - p_{j^0_{mk}mt}) + \beta(X^k_{jt} - X_{j^0_{mk}mt})$$

$$+ \sum_{n=0}^{t-2010} \mathbb{I}(\text{Periods Since Entry}_{jt} = n)\mu^{Fk}_n(y) + \sum_{n=0}^{t-2010} \mathbb{I}(\text{Periods Since Entry}_{jt} = n)\mu^k_n(y) + \phi_j + \epsilon_{jt}$$

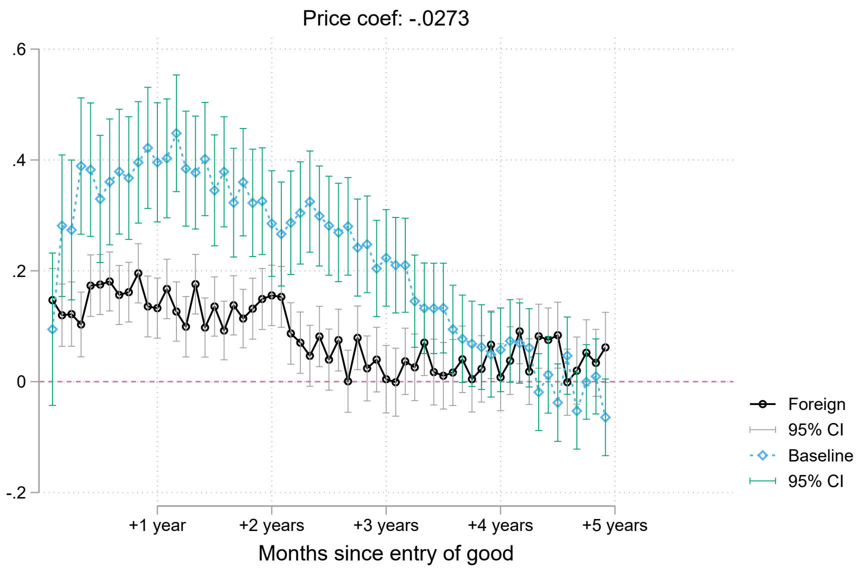

Figure 10: Rich people - products that have lasted 5 years

The age of a product impacts positively its share. This effect increases over time until about 3 years and then decreases. MNC products enjoy an even larger aging effect at first, but the premium declines over time, until it is zero.

9 Conclusion

Uncertainty about product quality may prevent consumers, particular consumers for whom it is costly to experiment, from purchasing products they don't know. This fundamental stickiness creates a demand barrier for young and small firms to grow. In this paper, I measure the importance of this issue by leveraging barcode-level dataset covering the universe of consumer packaged goods available in Mexico between 2010 and 2015. In this setting, uncertainty about product quality is an important issue and it creates a large advantage to global brands, who dominate the market despite charging higher prices.

I show five new stylized facts: domestic firms grow relatively more through surviving goods as opposed to new goods than foreign firms. Domestic products sales start lower but grow more and remain higher than initially, for a longer period than foreign products. Sales growth in the Mexican consumer goods sector is largely driven by the customer extensive margin. While this appears to be true for both domestic and foreign firms, for domestic firms customer growth is driven more by the intensive customer acquisition margin, within each product, as opposed to the extensive market acquisition margin, by adding products to the portfolio. Last, the new customers acquired by domestic products as they age are poorer than the initial customers who started purchasing the domestic products when it just came out, while the new customers of foreign products as they age are not different from the later customers.

I rationalize these five facts in a stylized model showing that the presence of uncertainty about product quality leads price-sensitive customers to withhold from purchasing a new good. Instead, they prefer to wait and learn from others, hurting firms' profit. Lastly, I provide evidence of the learning mechanisms at play. I show that individual learning matters by showing that a consumers' probability to consumer a given barcode from a brand increases with previous exposure to the brand, excluding the barcode itself, controlling for individual taste. This learning effect is much stronger for goods for which uncertainty is more salient, and it is lower for consumers in the bottom half of the expenditure distribution.

The findings in this paper suggest that uncertainty about product quality result in a lower demand for domestic products than otherwise. In future work, I plan to quantitatively estimate the size of the inefficiency, which will help us think about potential business strategies and policy interventions. Potential avenues for domestic firms to raise demand are informative advertising and dynamic pricing. Policy wise, interventions that raise minimum quality standards or transparency could also help develop the domestic sector.

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Appendix Figures

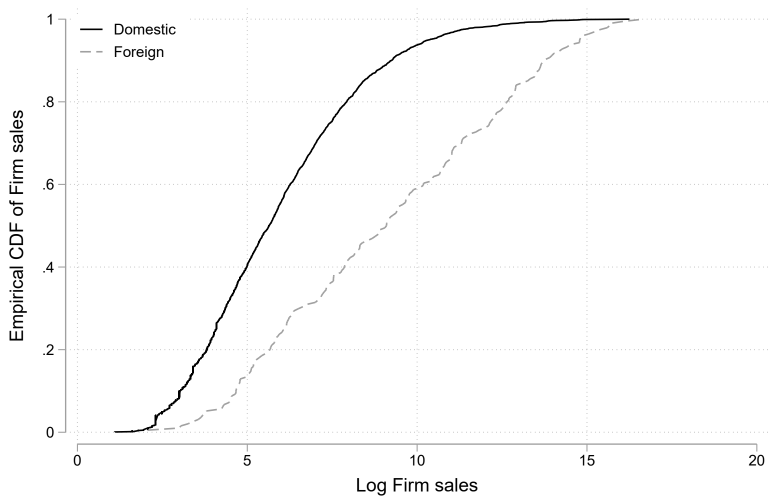


Figure A.1: Firm size distribution

Notes: Figure plots the distribution of the log sales of the firms observed in our dataset, where sales are defined as the total yearly expenditure of the households in that dataset on that firm. I separate out the distribution between foreign and domestic firms.

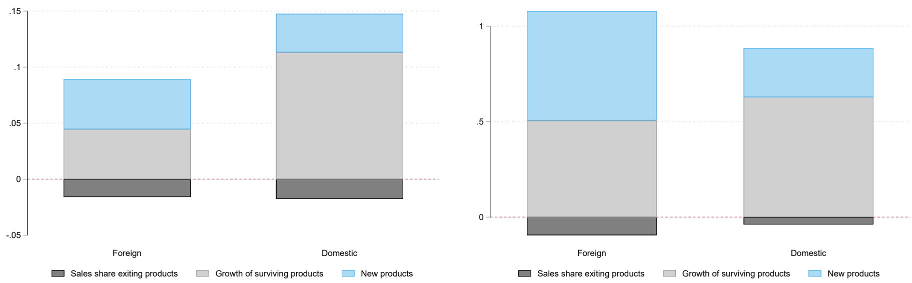


Figure A.2: Growth decomposition, by firm size

Notes: Figure represents the average firm-level year-to-year growth components, separated out by the origin of the firms. The sales of exiting products is the average share of sales that the product that exited between the previous year and the current year represented in the previous year. The growth of surviving products is the average growth rate of the total sales of products that survived between the previous year and the current year. The new products components is the product of the average rate of introduction of new products and the average sales of new products compared to older products. The left panel shows the decomposition for firms belonging to the top quarter of the firm sales distribution of each year. The right panel shows the decomposition for firms belonging to the bottom quarter of the firm sales distribution of each year.

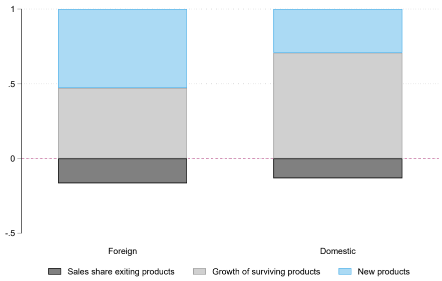


Figure A.3: Growth decomposition, relative terms

Notes: Figure represents the relative firm-level year-to-year growth components, separated out by the origin of the firms. The sales of exiting products is the average share of sales that the product that exited between the previous year and the current year represented in the previous year. The growth of surviving products is the average growth rate of the total sales of products that survived between the previous year and the current year. The new products components is the product of the average rate of introduction of new products and the average sales of new products compared to older products. Each component is then measured relative to the average growth rate of firm sales. The left panel shows the decomposition for firms belonging to the top quarter of the firm sales distribution of each year. The right panel shows the decomposition for firms belonging to the bottom quarter of the firm sales distribution of each year.

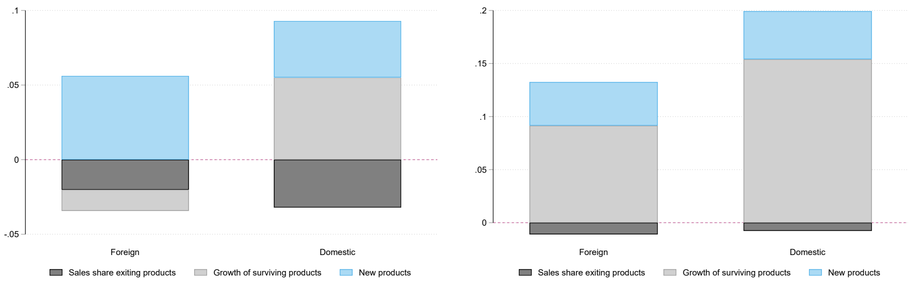


Figure A.4: Growth decomposition, by firm age

Notes: Figure represents the average firm-level year-to-year growth components, separated out by the origin of the firms. The sales of exiting products is the average share of sales that the product that exited between the previous year and the current year represented in the previous year. The growth of surviving products is the average growth rate of the total sales of products that survived between the previous year and the current year. The new products components is the product of the average rate of introduction of new products and the average sales of new products compared to older products. The left panel shows the decomposition for firms that are four years or older. The right panel shows the decomposition for firms that are less than four years old.

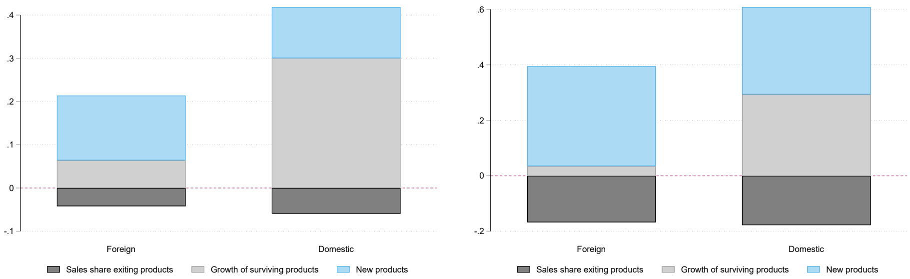


Figure A.5: Growth decomposition, by time horizon

Notes: Figure represents the average firm-level growth components, separated out by the origin of the firms, studying growth over two years (top panel) and over five years (bottom panel). The sales of exiting products is the average share of sales that the product that exited between the previous year and the current year represented in the previous year. The growth of surviving products is the average growth rate of the total sales of products that survived between the previous year and the current year. The new products components is the product of the average rate of introduction of new products and the average sales of new products compared to older products. The left panel shows the decomposition for firms belonging to the top quarter of the firm sales distribution of each year. The right panel shows the decomposition for firms belonging to the bottom quarter of the firm sales distribution of each year.

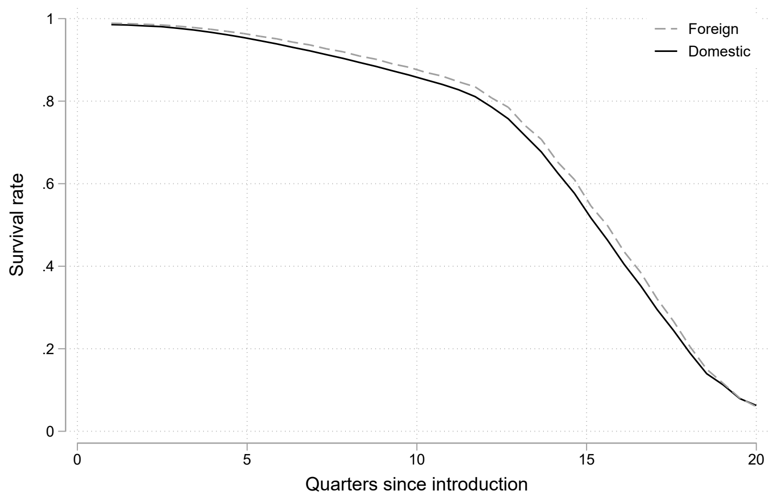


Figure A.6: Survival rate of foreign and domestic products, by quarter

Notes: Figure plots the survival rate of new products in the dataset over time, measured in quarters since the product was introduced. The death of a product is defined at the last quarter it appears in the dataset. I separate the survival rate by whether the product belongs to a foreign or a domestic firms.

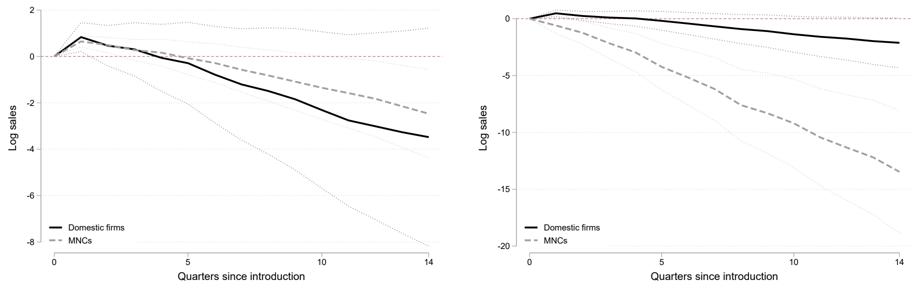


Figure A.7: Product life-cycle, by firm size

Notes: Figure represents the coefficients obtained on the dummies for the age of the product in quarters from a product-quarter level regression where I regress these dummies, quarter by product category fixed effects, and cohort fixed effects on the sales of a product in a given quarter. I run two separate regressions for domestic and foreign products, respectively. 95% confidence intervals are represented by the lighter lines. The left panel shows the results for products released by firms in the top quarter of the size distribution. The right panel shows the results for products released by firms in the bottom quarter of the size distribution.

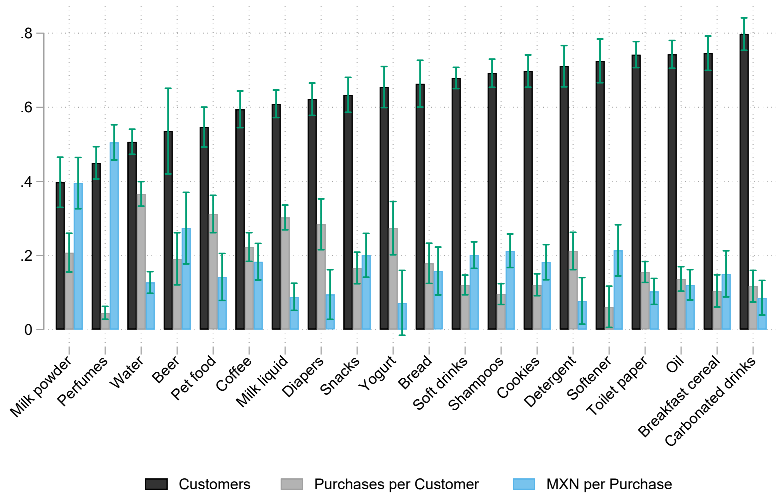


Figure A.8: Customer/Quantity/Value decomposition, by product category

Notes: Figure represents the coefficients obtained on log sales from firm-year-level regressions of log sales and year fixed effects on log customers, log purchases per customer and log monetary value per purchase. I run each of the three regressions separately for each of the top 20 product categories (one observation is the sales of a firm in a given a year in the category). 95% confidence intervals are represented using the bars.

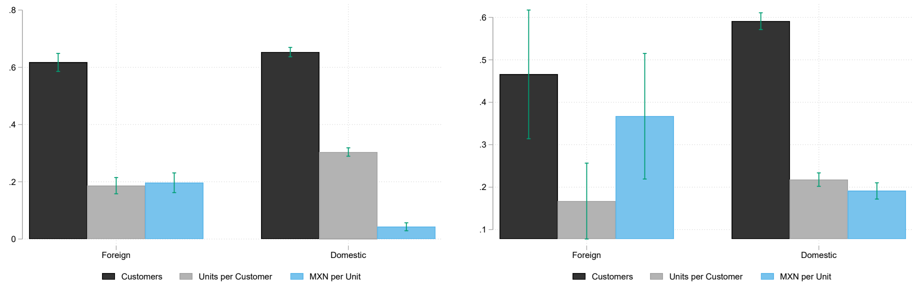


Figure A.9: Customer/Quantity/Value decomposition, by firm size

Notes: Figure represents the coefficients obtained on log sales from firm-year-level regressions of log sales, product category and year fixed effects on log customers, log units per customer and log monetary value per unit. I run each of the three regressions separately for foreign and domestic firms. 95% confidence intervals are represented using the bars. The left panel of this figure shows the results of the decomposition for firms in the top quarter of the firm size distribution while the right panel shows the results for firms in the bottom quarter of the firm size distribution.

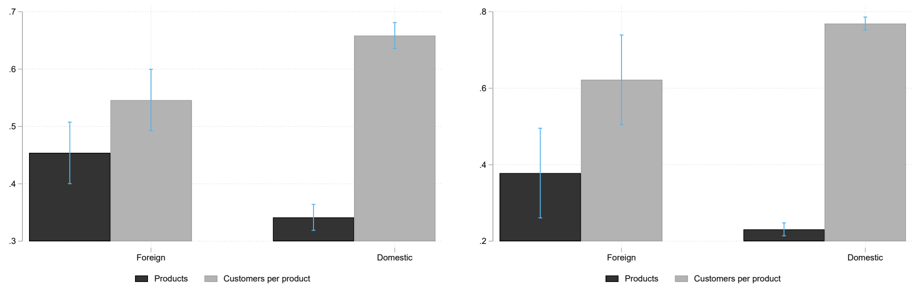


Figure A.10: Customer growth decomposition, by firm size

Notes: Figure represents the coefficients obtained on log customers from firm-year-level regressions of log customers, product category and year fixed effects on log products and log customers per product. I run each regression separately for foreign and domestic firms. 95% confidence intervals are represented using the bars. The left panel shows the decomposition for firms in the top quarter of the firm size distribution, and the right panel shows the decomposition for firms in the bottom quarter of the firm size distribution.

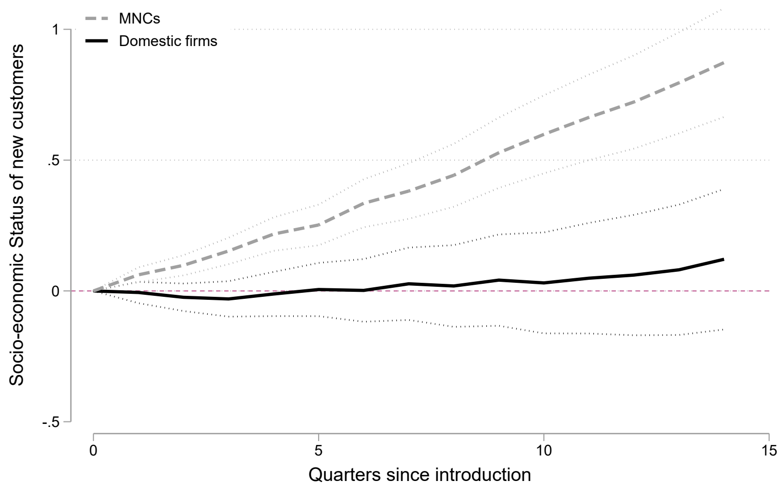


Figure A.11: Socio-economic status of new customers of older products (1-6)

Notes: Figure represents the coefficients obtained on the dummies for the age of the product in quarters from an individual-product-quarter level regression described in Equation (7) where I regress these dummies, quarter by product category fixed effects, cohort fixed effects and city fixed-effects on the average socio-economic status, measured on a scale from 1 to 6, of the new customers of a product in a given quarter. I run two separate regressions for domestic and foreign products, respectively. 95% confidence intervals are represented by the lighter lines.

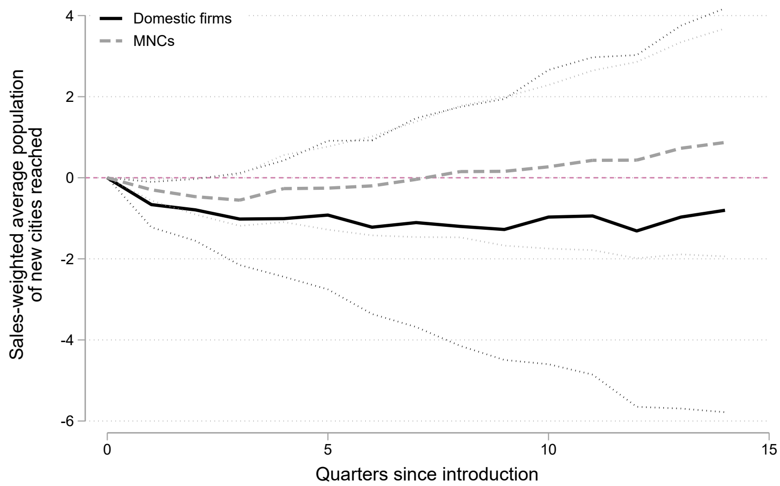
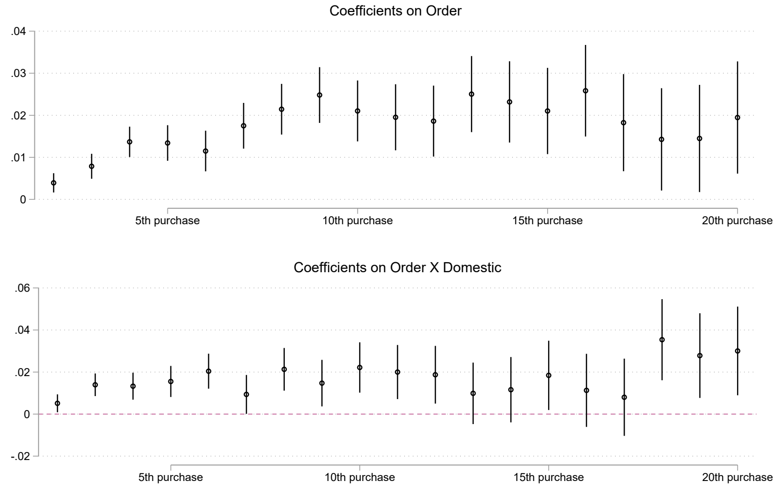
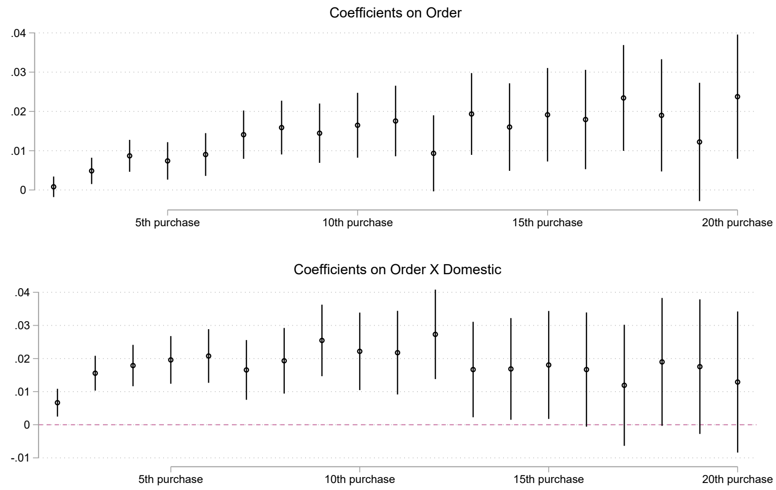


Figure A.12: New cities characteristics, by quarter and product type

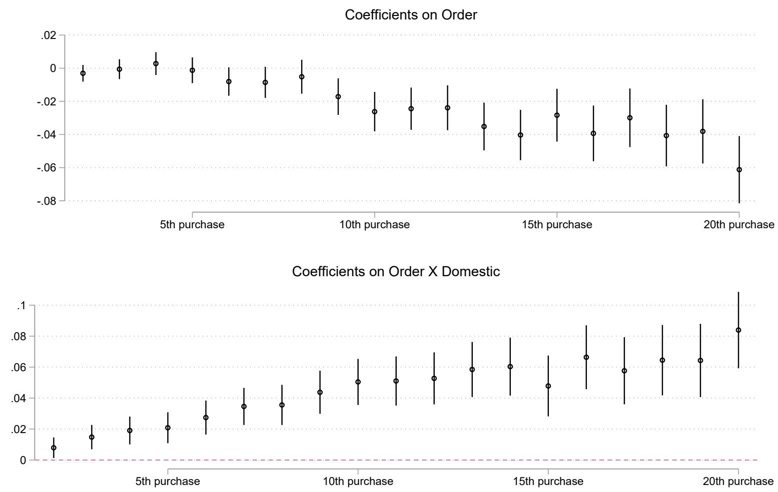
Notes: Figure represents the coefficients obtained on the dummies for the age of the product in quarters from a product-quarter level regression where I regress these dummies, quarter by product category fixed effects, and cohort fixed effects on the sales-weighted average of the population of the new cities in which a product sells in a given quarter. I run two separate regressions for domestic and foreign products, respectively. 95% confidence intervals are represented by the lighter lines.



(a) Products defined as firm-brand-category-4 characteristics



(b) Products defined as firm-brand-category-2 characteristics



(c) Products defined as firm-brand-category

Figure A.13: Evidence of learning behavior, robustness by size

Notes: Figures show the results of a purchase-household level regression, for products purchased up to 20 times, of the size of the product (defined as firm-brand- category-4 characteristics in Panel (a), 2 characteristics in Panel (b) and simply firm-brand-category in Panel (c)) chosen during the purchase, on dummies describing the order in which the product was purchased by the household (coefficients shown in the top panel) and on dummies interacting the order and the fact that the good is produced by a domestic firms (coefficients shown in the bottom panel). I only keep products that are new relative to the dataset. I always control for household fixed effects, product fixed effects and year fixed effects. Standard errors are reported in parenthesis.

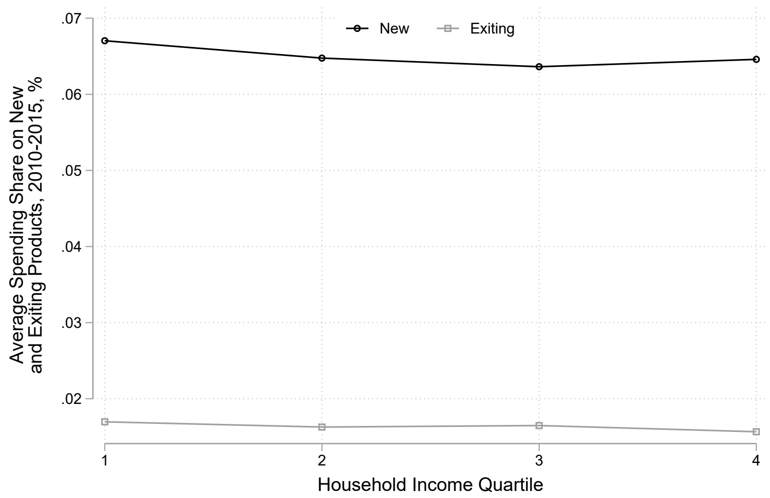


Figure A.14: Spending share on new and exiting products, by household income quartile

Notes: Figure reports spending on new and exiting products across households groups and across the universe of products.

Appendix Tables

	ENIGH			KWP			Difference	
	mean	sd	N	mean	sd	N	diff	p
Number of household members	3.94	1.98	26942	4.37	1.83	8414	0.430	0.00
Number of women in household	2.03	1.27	26942	2.29	1.22	8414	0.267	0.00
Age head of household	48.32	15.62	26942	45.61	14.02	8412	-2.707	0.00
Finished primary	0.84	0.37	26942	0.96	0.20	8414	0.120	0.00
Finished secondary	0.35	0.48	26942	0.65	0.48	8414	0.307	0.00
Finished Post-secondary	0.26	0.44	26942	0.13	0.34	8414	-0.130	0.00
Works full time	0.75	0.44	26942	0.75	0.43	8414	0.006	0.24
Number of cars	0.53	0.80	26942	0.56	0.66	8414	0.030	0.00
Number of PCs	0.31	0.61	26942	0.33	0.47	8414	0.019	0.01
Access to Internet (0/1)	0.19	0.39	26942	0.24	0.42	8414	0.043	0.00
Number of color TVs	1.44	0.92	26942	1.87	0.98	8413	0.426	0.00
Number of fridges	0.83	0.43	26942	0.96	0.19	8412	0.135	0.00
Number of microwaves	0.42	0.51	26942	0.70	0.46	8414	0.287	0.00
Number of bedrooms	2.01	0.97	26385	2.20	0.97	8412	0.188	0.00
Debit or credit card (0/1)	0.21	0.41	26942	0.28	0.45	8414	0.070	0.00
Monthly expenditure (MXN)	1107.30	758.20	26942	1320.09	736.49	8414	212.796	0.00

Table B.1: Household-level summary statistics, KWP vs ENIGH in 2010

Notes: Table compares summary statistics of the main dataset used in the analysis (Kantar World Panel or KWP) in 2010 in Columns (4)-(6) against the official expenditure survey (ENIGH 2010) in Columns (1)-(3). ENIGH provides the national reference values for household characteristics, income and expenditures. When relevant, the variable described is measured for the head of household (adult man if two working-age adults are present). Ownership of a debit or credit card is a variable in the ENIGH survey and it is coded in the KWP to 1 if the household is ever reported to use a card as a mode of payment. Expenditure in the ENIGH survey cannot be compared exactly to expenditure in the KWP but is constructed based on similar categories (spending on personal care, household care, and food for at-home consumption).

	Log unit price of rice in				
	Ghana	Nigeria	Niger	Timor Leste	Yemen
	(1)	(2)	(3)	(4)	(5)
Imported	0.356	0.280	0.367	0.037	0.199
	(0.010)	(0.016)	(0.102)	(0.011)	(0.012)
Geographical FEs	Yes	Yes	No	Yes	No
Indiv FEs	No	No	Yes	No	Yes
Years covered	2005-2017	2015-2018	2011, 2014	2001, 2008	2005
Mean of Dep. Var.	3.25	5.35	4.87	-0.15	5.37
R2	0.81	0.26	0.23	0.09	0.53
N	7983	25760	2002	4489	3044

Table B.2: Imported goods cost a lot more in developing countries

Note: data comes from LSMS surveys financed by the World Bank and subsequent rounds of surveys run by the national statistical agencies of each country. I kept the items which were described by their country of origin and for which both a “foreign” item and a “domestic” item was available according to the survey. I then computed the unit price by dividing the total price reported by the total quantity reported. Then for each country and each item I regressed the log unit price on a dummy for whether the good was imported, a time dummy and regional dummies.

	All	Mexican	Foreign
Growth sales	0.11	0.14	0.08
	(0.35)	(0.48)	(0.17)
Product Life Cycle Component	0.06	0.10	0.03
Growth of Surviving	0.08	0.12	0.04
	(0.32)	(0.45)	(0.17)
Sales Share of Exit	-0.02	-0.02	-0.02
	(0.04)	(0.05)	(0.04)
New Products Component	0.04	0.04	0.04
Entry Rate	0.16	0.16	0.16
	(0.12)	(0.15)	(0.09)
Entrants Relative Sales	0.26	0.24	0.27
	(0.28)	(0.31)	(0.26)
Obs	8885	8010	875

Table B.3: Firm growth decomposition

Notes: Table shows the results from the decomposition of annual growth of sales at the firm-year level, as defined in Equation (3). For each firm and year starting in 2011, I compute the contribution of new products the number of new products and their sales in their first year of activity. Table shows the sales-weighted average across all firms and years. The first column groups all firms, while the second and third column separate firms by whether they have received foreign investment ("Foreign") or not ("Mexican"). Standard errors are shown in parenthesis.

	Log sales				Log quantities		Log price	
	Foreign	Domestic	Foreign	Domestic	Foreign	Domestic	Foreign	Domestic
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age=2 quarters	0.659	1.051	0.660	1.067	0.541	0.969	0.158	0.055
	(0.079)	(0.092)	(0.079)	(0.089)	(0.080)	(0.094)	(0.037)	(0.038)
Age=3 quarters	0.558	1.319	0.561	1.356	0.322	1.162	0.308	0.085
	(0.111)	(0.125)	(0.111)	(0.121)	(0.111)	(0.127)	(0.052)	(0.051)
Age=4 quarters	0.422	1.543	0.426	1.601	0.063	1.278	0.446	0.121
	(0.149)	(0.166)	(0.149)	(0.161)	(0.149)	(0.168)	(0.070)	(0.068)
Age=5 quarters	0.276	1.796	0.282	1.872	-0.194	1.437	0.599	0.157
	(0.190)	(0.209)	(0.190)	(0.203)	(0.190)	(0.212)	(0.089)	(0.086)
Age=6 quarters	0.055	1.967	0.062	2.061	-0.528	1.498	0.732	0.203
	(0.232)	(0.255)	(0.232)	(0.247)	(0.232)	(0.257)	(0.109)	(0.104)
Age=7 quarters	-0.142	2.088	-0.134	2.201	-0.848	1.514	0.877	0.238
	(0.274)	(0.301)	(0.274)	(0.292)	(0.275)	(0.304)	(0.129)	(0.123)
Age=8 quarters	-0.393	2.236	-0.383	2.367	-1.209	1.546	1.016	0.283
	(0.317)	(0.348)	(0.317)	(0.337)	(0.318)	(0.351)	(0.149)	(0.142)
Age=9 quarters	-0.617	2.396	-0.606	2.546	-1.554	1.605	1.171	0.316
	(0.360)	(0.395)	(0.360)	(0.383)	(0.361)	(0.398)	(0.169)	(0.161)
Age=10 quarters	-0.825	2.542	-0.813	2.710	-1.888	1.625	1.305	0.364
	(0.404)	(0.442)	(0.404)	(0.429)	(0.404)	(0.446)	(0.189)	(0.180)
Age=11 quarters	-1.061	2.630	-1.047	2.817	-2.227	1.630	1.447	0.404
	(0.446)	(0.488)	(0.446)	(0.474)	(0.447)	(0.493)	(0.210)	(0.199)
Age=12 quarters	-1.267	2.745	-1.252	2.949	-2.544	1.621	1.566	0.461
	(0.490)	(0.536)	(0.490)	(0.520)	(0.491)	(0.541)	(0.230)	(0.219)
Age=13 quarters	-1.479	2.876	-1.461	3.098	-2.858	1.613	1.723	0.500
	(0.534)	(0.584)	(0.534)	(0.566)	(0.535)	(0.589)	(0.251)	(0.238)
Age=14 quarters	-1.706	2.999	-1.688	3.243	-3.228	1.646	1.843	0.569
	(0.578)	(0.632)	(0.578)	(0.614)	(0.579)	(0.638)	(0.271)	(0.258)
Age=15 quarters	-1.972	3.135	-1.952	3.401	-3.583	1.677	2.012	0.597
	(0.623)	(0.681)	(0.623)	(0.661)	(0.623)	(0.687)	(0.292)	(0.278)
Firm sales, mMXN			0.007	0.164				
			(0.004)	(0.006)				
Product X Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FEs	No	No	No	No	Yes	Yes	Yes	Yes
Initial quarter mean	5.47	4.71	5.47	4.71	5.47	4.71	5.47	4.71
N	16836	12424	16836	12424	16678	12173	16678	12173
R2	0.23	0.28	0.23	0.32	0.33	0.30	0.56	0.59

Table B.4: Barcode life-cycle: log sales

Notes: Table shows the results from the product-quarter-level regression shown in Equation (4) of dummies for the age of the product in quarters, product interacted with quarter fixed effects, cohort fixed effects and sometimes firm-level sales on log sales (Columns (1)-(4)), log quantities (Columns (5) and (6)) or log price (Columns (7) and (8)). I only keep products that survived at least 14 quarters and compute their total sales or quantities, or sales-weighted price in the dataset in each quarter. Standard errors are shown in parenthesis.

	Within firms across time			Across firms within time		
	Customers	Items per C	MXN per item	Customers	Items per C	MXN per item
Mexican firms	0.626	0.176	0.198	0.736	0.200	0.064
	(0.005)	(0.003)	(0.005)	(0.003)	(0.002)	(0.003)
N	10934	10934	10934	12081	12081	12081
R2	0.97	0.90	0.86	0.81	0.43	0.03
	Within firms across time			Across firms within time		
	Customers	Items per C	MXN per item	Customers	Items per C	MXN per item
Foreign firms	0.582	0.141	0.277	0.795	0.205	0.000
	(0.015)	(0.008)	(0.015)	(0.007)	(0.005)	(0.008)
N	1126	1126	1126	1157	1157	1157
R2	0.99	0.97	0.90	0.91	0.61	0.00

Table B.5: Sales decomposition

Notes: Table shows the results of the firm-year-level decomposition of sales as explained in Equation (5a). On the left-hand side, I show the coefficients obtained on each firm-level regressions of the log of sales and firm and year fixed effects on the log number of customers, log number of items sold to each customer, and log monetary value of each item sold. The regressions are computed separately for Mexican and Foreign firms, respectively. I show these results graphically in Figure 5. On the right-hand side, I show the coefficients obtained from three similar regressions without firm fixed effects, which amounts to considering each observation as a separate firm and interpreting the coefficient as heterogeneity across firms. Standard errors are shown in parenthesis.

	Within firms across time		Across firms within time	
	Products	Customers per P	Products	Customers per P
Mexican firms	0.284	0.716	0.474	0.526
	(0.005)	(0.005)	(0.003)	(0.003)
N	11273	11273	12599	12599
R2	0.95	0.95	0.67	0.72
	Within firms across time		Across firms within time	
	Products	Customers per P	Products	Customers per P
Foreign firms	0.458	0.542	0.626	0.374
	(0.017)	(0.017)	(0.008)	(0.008)
N	1150	1150	1186	1186
R2	0.98	0.96	0.82	0.63

Table B.6: Customers decomposition

Notes: Table shows the results of the firm-year-level decomposition of the number of customers as explained in Equation (6a). On the left-hand side, I show the coefficients obtained on each firm-level regressions of the log of number of customers and firm and year fixed effects on the log number of products and log customers buying each product. The regressions are computed separately for Mexican and Foreign firms, respectively. I show these results graphically in Figure 6. On the right-hand side, I show the coefficients obtained from two similar regressions without firm fixed effects, which amounts to considering each observation as a separate firm and interpreting the coefficient as heterogeneity across firms. Standard errors are shown in parenthesis.

	Log expenditure						SES (1-6)	
	Foreign	Domestic	Foreign	Domestic	Foreign	Domestic	Foreign	Domestic
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age=2 quarters	0.011	0.002	0.014	-0.005	0.014	-0.005	0.093	0.008
	(0.008)	(0.012)	(0.007)	(0.011)	(0.007)	(0.011)	(0.018)	(0.027)
Age=3 quarters	0.012	-0.005	0.015	-0.017	0.016	-0.017	0.140	-0.020
	(0.010)	(0.015)	(0.009)	(0.014)	(0.009)	(0.014)	(0.023)	(0.033)
Age=4 quarters	0.024	-0.030	0.029	-0.051	0.030	-0.052	0.209	-0.031
	(0.013)	(0.018)	(0.012)	(0.018)	(0.012)	(0.018)	(0.030)	(0.042)
Age=5 quarters	0.045	-0.025	0.053	-0.055	0.054	-0.055	0.285	-0.027
	(0.016)	(0.023)	(0.015)	(0.022)	(0.015)	(0.022)	(0.038)	(0.052)
Age=6 quarters	0.060	-0.051	0.067	-0.077	0.069	-0.077	0.340	-0.033
	(0.020)	(0.027)	(0.018)	(0.026)	(0.018)	(0.026)	(0.046)	(0.062)
Age=7 quarters	0.066	-0.057	0.080	-0.087	0.082	-0.087	0.439	-0.059
	(0.023)	(0.032)	(0.022)	(0.030)	(0.022)	(0.030)	(0.054)	(0.073)
Age=8 quarters	0.092	-0.075	0.110	-0.107	0.112	-0.107	0.495	-0.039
	(0.027)	(0.037)	(0.025)	(0.035)	(0.025)	(0.035)	(0.063)	(0.084)
Age=9 quarters	0.105	-0.090	0.123	-0.122	0.125	-0.122	0.568	-0.052
	(0.030)	(0.041)	(0.028)	(0.039)	(0.028)	(0.039)	(0.071)	(0.094)
Age=10 quarters	0.119	-0.111	0.139	-0.141	0.142	-0.141	0.678	-0.041
	(0.034)	(0.046)	(0.032)	(0.044)	(0.032)	(0.044)	(0.079)	(0.105)
Age=11 quarters	0.131	-0.123	0.158	-0.154	0.161	-0.154	0.755	-0.076
	(0.037)	(0.051)	(0.035)	(0.049)	(0.035)	(0.049)	(0.087)	(0.116)
Age=12 quarters	0.148	-0.147	0.179	-0.182	0.182	-0.182	0.832	-0.069
	(0.041)	(0.056)	(0.039)	(0.053)	(0.039)	(0.053)	(0.096)	(0.128)
Age=13 quarters	0.172	-0.155	0.203	-0.187	0.207	-0.187	0.909	-0.079
	(0.045)	(0.061)	(0.042)	(0.058)	(0.042)	(0.058)	(0.104)	(0.139)
Age=14 quarters	0.192	-0.166	0.226	-0.197	0.229	-0.198	0.999	-0.078
	(0.048)	(0.066)	(0.045)	(0.063)	(0.046)	(0.063)	(0.113)	(0.150)
Age=15 quarters	0.204	-0.165	0.240	-0.205	0.244	-0.207	1.082	-0.033
	(0.052)	(0.071)	(0.049)	(0.067)	(0.049)	(0.067)	(0.122)	(0.162)
Firm sales, mMXN					0.001	0.013		
					(0.001)	(0.003)		
Product X Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FEs	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Initial quarter mean	9.76	9.72	9.76	9.72	9.76	9.72	2.43	2.38
N	447113	219106	447113	219106	447113	219106	447113	219106
R2	0.02	0.03	0.13	0.13	0.13	0.13	0.05	0.05

Table B.7: Barcode life-cycle: characteristics of new customers

Notes: Tables represents the coefficients obtained on the dummies for the age of the product in quarters from a individual-product-quarter level regression described in Equation (7) where I regress these dummies, quarter by product category fixed effects and cohort fixed effects on the annual expenditure of the new customers of a product in a given quarter. In Columns (1) and (2) I don't have city fixed effects. In Columns (3) and (4) I add city fixed effects, and these are the coefficients which are represented in Figure 7. In Columns (5) and (6) I look at consumers' socio-economic status, which is an integer between 1 (lowest) and 6 (highest). For each outcome, I run two separate regressions for foreign and domestic products, respectively. Standard errors are shown in parenthesis.

	Log population		Log density		Log distance to CDMX	
	Foreign	Domestic	Foreign	Domestic	Foreign	Domestic
	(1)	(2)	(3)	(4)	(5)	(6)
Age=2 quarters	-0.610	-0.324	-0.534	-0.467	-0.048	-0.180
	(0.211)	(0.424)	(0.192)	(0.379)	(0.127)	(0.260)
Age=3 quarters	-0.786	-0.369	-0.856	-0.595	-0.068	0.013
	(0.306)	(0.633)	(0.278)	(0.569)	(0.182)	(0.381)
Age=4 quarters	-0.855	-0.562	-0.776	-0.998	-0.153	0.619
	(0.420)	(0.900)	(0.379)	(0.804)	(0.246)	(0.535)
Age=5 quarters	-0.944	-0.470	-0.895	-1.053	-0.165	0.507
	(0.548)	(1.194)	(0.493)	(1.057)	(0.320)	(0.702)
Age=6 quarters	-1.023	-0.444	-0.660	-1.238	-0.249	0.787
	(0.668)	(1.474)	(0.598)	(1.302)	(0.388)	(0.864)
Age=7 quarters	-1.066	-0.406	-0.712	-1.652	-0.370	1.514
	(0.787)	(1.778)	(0.705)	(1.561)	(0.457)	(1.035)
Age=8 quarters	-1.222	-1.299	-0.659	-1.631	-0.448	1.072
	(0.918)	(2.065)	(0.821)	(1.821)	(0.532)	(1.208)
Age=9 quarters	-1.263	-0.754	-0.873	-1.949	-0.292	2.068
	(1.036)	(2.326)	(0.928)	(2.059)	(0.600)	(1.364)
Age=10 quarters	-1.230	-0.384	-0.839	-1.938	-0.434	2.144
	(1.162)	(2.618)	(1.039)	(2.312)	(0.673)	(1.533)
Age=11 quarters	-1.646	-1.442	-0.862	-2.082	-0.467	2.006
	(1.285)	(2.925)	(1.151)	(2.574)	(0.745)	(1.706)
Age=12 quarters	-1.614	-0.828	-0.740	-2.621	-0.458	2.533
	(1.418)	(3.229)	(1.268)	(2.835)	(0.820)	(1.879)
Age=13 quarters	-1.732	-1.199	-0.945	-2.550	-0.351	2.516
	(1.550)	(3.501)	(1.384)	(3.088)	(0.896)	(2.047)
Age=14 quarters	-2.143	-0.575	-1.173	-3.419	-0.453	3.174
	(1.681)	(3.792)	(1.502)	(3.352)	(0.972)	(2.221)
Age=15 quarters	-1.911	0.677	-1.092	-2.128	-0.437	3.016
	(1.812)	(4.087)	(1.616)	(3.607)	(1.046)	(2.391)
Product X Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FEs	Yes	Yes	Yes	Yes	Yes	Yes
Initial quarter mean	14.14	14.22	5.26	5.26	6.01	5.97
N	4673	1802	5502	2151	5370	2093
R2	0.16	0.25	0.11	0.18	0.11	0.17

Table B.8: Barcode life-cycle: log sales-weighted average characteristics of new cities

Notes: Tables represents the coefficients obtained on the dummies for the age of the product in quarters from a product-quarter level regression described in Equation (7) where I regress these dummies, quarter by product category fixed effects, and cohort fixed effects on the average population of the new cities reached by a product in a given quarter in Columns (1) and (2). For each outcome, I run two separate regressions for foreign and domestic products, respectively. In Columns (3) and (4), I reproduce the regressions ran in Columns (1) and (2) with the average income per capita of the new cities and in Columns (5) and (6) with the poverty rate of the new cities. Standard errors are shown in parenthesis.