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Neighborhood Shops vs. Convenience Chains

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Abstract

Hundreds of millions of microenterprises in emerging economies face increased competition from the entry and expansion of large firms that offer similar products. This paper studies how one of the world's most prevalent microenterprises, neighborhood shops, confront competition from convenience chains (e.g., 7-Eleven) in Mexico. To address the endogeneity in time and location of chain store openings, I pair two-way fixed effects with a novel instrument that, at the neighborhood level, shifts the profitability of chains but not of shops. An expansion from zero to the average number of chain stores in a neighborhood reduces the number of shops by 15%. This reduction is not driven by increased shop exits but by decreased shop entries. Shops retain their sales of fresh products and 96% of their customers, but customers visit shops less often and spend less on non-fresh and packed goods. The evidence suggests that shops survive by exploiting comparative advantages stemming from being small and owner-operated, such as lower agency costs, relationships with the community, broader and tailored product mix, and informal credit. The welfare gains of convenience chains replacing shops are increasing in household income.

Keywords: development, microenterprise dynamics, competition, entry

JEL Classification: O10, D22, D25, D40

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1 Introduction

A stunning 214 million microenterprises account for 84% of all firms, 40% of employment, and 21% of value-added in developing countries (SME Finance Forum, 2019). These firms are not only an essential source of (self-)employment and income, but they also provide access to goods and services for the poor. As economies develop, these small firms face increased competition, even an existential threat, from large and more efficient corporations with similar and often identical products. Despite this threat, microenterprises continue to exist in overwhelming numbers (Hsieh and Olken, 2014; Atkin et al., 2019), a phenomenon consistent with the literature documenting significant misallocation of resources in developing countries (e.g., Hsieh and Klenow, 2009).

This phenomenon raises the question of to what extent competition from large firms leads to reallocation through the exit of microenterprises and how the surviving small firms compensate for disadvantages in scale. Until recently, even measurements of small firm death were limited. McKenzie and Paffhausen (2019) collate data from over 14,000 firms in developing countries to establish stylized facts on small firm death, finding that the lead cause of microenterprise death is making a loss (41%). Nonetheless, many mechanisms make firms unprofitable, such as increased input costs, demand drops, poor management practices, and new competitors. This paper studies a potentially key mechanism driving microenterprises' entry and exit dynamics: the effect of increased competition from large firms.

Data availability and identification are the two main challenges in estimating the effect of competition from large firms on microenterprises. The pressing concern regarding data is that it is scarce concerning microenterprises because surveys and censuses often only cover firms of at least a certain size.[1] Regarding identification, the most salient issue is that large firms' entry time and location are endogenous and likely correlated with performance measures of incumbent microenterprises.

To address data availability challenges, I study one of the most prevalent microenterprises, sole-proprietor neighborhood shops (henceforth shops). Shops are commonplace in developing countries. For example, in Mexico, there are 600 thousand *tienditas*; in the Philippines, there are 1.3 million *sari-sari*; and in India, there are 12 million *kiranas* (Economic Times, 2019; Philstar, 2017). Across the globe, shops share common characteristics, such as being small and primarily owner-operated, offering a wide variety of food and drinks, and having their neighbors as their primary customers. I study the context of Mexico, where shops are vital to the economy. They represent one out of every eight firms and 4% of total employment, and they have the largest market share in the food and beverages industry, 31%.[2]

In the last two decades, shops in Mexico faced increased competition from the entry and expansion of convenience chains (e.g., 7-Eleven) that expanded from fewer than 2,000 stores to more than 23,000. These convenience chains (henceforth chains) are direct competitors to shops because they significantly overlap in their product offerings, are small in size per store, and mainly capture incidental purchases. Chains have advantages over shops due to their economies of scale, which allow them to share costs across their stores, better bargain with suppliers, have lower financing costs, and have more productivity-enhancing investments. Chains may also represent lower search costs to consumers because of their store uniformity within each chain and location on wide streets with big signs. However, shops may have comparative advantages, such as their relationships with the neighbors, offering informal credit, having lower agency costs (few or no employees), and not paying taxes.

[1] For example, India's Annual Survey of Industries covers firms with at least 10 workers, and China's Annual Surveys of Industrial Production covers non-state firms with more than 5 million Yuan in revenue Hsieh and Klenow (2009).

[2] Source: Economic Census 2019 and ENIGH 2018. Supermarkets have 17%, food markets 20%, specialized stores (e.g., bakeries, *tortillerias*, rotisseries) 30%, and convenience chains 2%.

To measure the impact of chains' expansion on shops, I assembled a rich microdata collection, including confidential performance measures, such as revenue and profits, for the universe of shops in Mexico between 1999 and 2019.[3] I link these detailed firm data with household income and expenditure surveys spanning from 2006 to 2018, which include information on what households buy, where they buy it, and how much they pay for it.

Even with rich data, estimating chains' impact on shops is challenging because chains' entry time and location are endogenous. Neighborhoods with higher demand for the products offered by both shops and chains will have better outcomes for shops and be more attractive for chains to enter. For example, a new park in a neighborhood may increase foot traffic and demand for drinks and snacks for both shops and chains. These unobservable shocks that increase or decrease demand for chains and shops will upward bias ordinary least squares estimates, even after controlling for city-wide trends and neighborhood time-invariant characteristics.

I pair city-year and neighborhood fixed effects with an instrumental variable that shifts the profitability of chains but not of shops and varies across neighborhoods and time to address the endogeneity in chains' entry. The instrument leverages the complementarity between two critical differences between chains and shops that are also prominent drivers of chains' entry. First, chains exploit the advantages of opening stores in nearby cities, such as same-chain stores sharing distribution centers, trucks, inspectors, and regional offices. This cost-sharing in distribution, transportation, marketing, overhead, and other costs reduces chains' average costs and makes each store more profitable, leading to regional economies of scale for each chain. I measure these economies of scale using a Herfindahl-Hirschman index without normalization, which increases with the number of chain stores in adjacent cities and their concentration. Second, unlike shops primarily located next to the owners' houses, chains open on wide streets to target driving and bus-riding customers. I measure the neighborhood's suitability for chains using the prevalence of wide streets.

The instrument is the interaction between the measure of economies of scale, which varies across time and cities, and the neighborhood's prevalence of wide streets, which varies within cities. Causal identification relies on more stores of chain X in cities near city A, making neighborhoods suitable for chains in city A more profitable for chain X because of cost-sharing and chain-specific regional economies of scale. However, more stores of chain X in cities near city A do not affect the profitability of incumbent shops in city A, except for the increased probability of a chain opening in their neighborhood.

A natural concern with the instrumental variable strategy is that regions with economic booms will have more entries of chains and will also be more profitable for shops. City-year fixed effects control for these city-wide trends. However, economic booms in the region would still be an issue if they resulted in more chains in neighborhoods with more wide streets and if these neighborhoods were the ones where household income grew the fastest. In particular, the problem would be that the instrument would be correlated with household income, hence with demand faced by shops, violating the exclusion restriction. I show this is not the case. First, I show that regional economies of scale drive the entry of chain stores and that these economies of scale are firm-specific, not region- or city-specific. Second, I show that the instrument does not correlate with customers' (neighbors') characteristics that likely affect demand, such as income, number of cars, expenses, and demographics. Third, I show that while the instrument is correlated with the number of shops and convenience chains, it is not correlated with the number of other retail establishments, such as supermarkets. The empirical section discusses other potential concerns in more detail and the analyses

[3]Economic censuses cover all establishments in the country. Establishments that are not covered are those that open and close in between census waves.

conducted to address them.

I organize the main results into three categories. First, I find that each additional chain store in a neighborhood reduces the number of shops by 3.85, implying that an expansion from zero to the average number of chain stores in a neighborhood (6.7) reduces the number of shops by 15%. The number of exits of shops does not increase, making the 16% reduction in the number of shop entries the main driver of the decrease in the number of shops. Second, the adverse effects on shops' performance concentrate along the extensive margin. At the neighborhood level, shops' total profits, revenue, value-added, inventories, total employed, and total hours worked decline between 20 and 30%. However, these adverse effects are less than a third in magnitude at the shop level (intensive margin), between 0 and 7%.

Third, I find that customers continue to purchase in shops, but they do so less and less often. An expansion of chain stores from zero to their average number in a neighborhood decreases the probability of neighbors purchasing in shops by 3.5%. Those who continue to purchase in shops do so 9% less often and buy 10% less. The effect on neighbors' purchases differs across product categories. Chains do not affect household expenditure in shops on fresh products such as fresh pastries, fruit, and vegetables, which are often sourced daily by shop owners from central markets. Still, chains decrease household purchases in shops of packed and standardized products like sodas, milk, and bottled juices by 15%.

Why do shops survive? To answer this question, first, I estimate a conditional discrete choice model to understand what drives the decision to purchase in a neighborhood shop instead of a convenience chain. Within the same census tract, households are more likely to purchase in the neighborhood shop if it is closer, they are buying fresh products, they own their home, or they are using informal credit to pay. On the other hand, they are more likely to purchase in the chain if they are using electronic payments, they are buying alcohol and tobacco, they own a car, or they are richer. Motivated by these drivers, I study the heterogeneity of the effect of chains on shops and find evidence consistent with shops having meaningful comparative advantages. Shops less affected by chains are smaller and owner-operated, whose comparative advantages include facing lower agency costs, building relationships with their customers, tailoring their product mix, and screening their neighbors to provide them with informal credit to buy in the shop.

Regarding agency costs, shops have an advantage because the owner is the residual claimant of profits, which makes the owner's incentives more aligned to the firm's than employees' incentives. Consistently, shops do not lose revenue in products where effort has a higher return (products that are harder to source and ensure quality, such as fresh products). Consumers continue to spend as much on these products in shops, even after the decrease in the number of shops. Regarding relationships and informal credit, shops have a central role in providing credit for purchases of food and beverages, especially for lower-income households. Shops supply 16% of the credit used to purchase food and drinks in Mexico, but 69% of the credit used to buy food and beverages for families in the first income quintile. In a context where consumers are both credit and cash-constrained, being able to screen customers and offer informal credit to buy in the store becomes a critical advantage.

The expansion of chains that, in turn, reduces the number of neighborhood shops can positively and negatively affect welfare. On the one hand, chains reduce the profits of shop owners and decrease the availability of shops for consumers. On the other hand, chains create jobs and offer products and amenities that may not have been available in shops. I use the framework of Atkin, Faber and Gonzalez-Navarro (2018) to decompose the welfare effects of the expansion of chains into three effects on the household cost of living and two effects on nominal household incomes. I find that differences in amenities between chains and shops are the main drivers of the welfare effects. The poor, who value the products and amenities in neighborhood shops the most, have the largest welfare loss from their reduced availability. In contrast, the rich have the largest gains from the amenities now offered by convenience chains, making the welfare gains of chains substituting shops regressive. Regarding the income effects, they mostly cancel each other out because labor income from new jobs at convenience chains compensates for most of the lost income from shop owners' profits.

This paper contributes to two strands of literature. First, it contributes to the literature on competition in developing countries by introducing a novel instrument and micro-level data on more than one million shops across 20 years to measure the response of one of the smallest firms, the shop, to competition from some of the largest companies in Mexico that operate hundreds, even thousands, of small convenience stores.[4] Other papers in this literature include Bergquist and Dinerstein (2020), which studies competition among produce traders in Kenyan markets. They randomized cash subsidy offers for potential entrants to enter and sell in the treated markets. The take-up rate was between 12 and 42%, but entry had negligible effects on prices. Busso and Galiani (2019) randomized the entry of 61 firms into 72 markets serving beneficiaries of a conditional cash transfer program in the Dominican Republic and found that entry led to reductions in prices ranging from 2 to 6 percent and an improvement in self-reported quality. Macchiavello and Morjaria (2020) find that mills in more suitable areas in Rwanda face more competition and have fewer relational contracts with farmers. An additional competing mill makes farmers worse off due to competition hampering relational contracts between farmers and coffee mills. Different from these three papers, where competing firms are fairly similar, in Jensen and Miller (2018) boat builders are heterogeneous in quality, and market integration leads to better outcomes for high-quality builders and exits for low-quality ones.

Bao and Chen (2018) and Atkin, Faber and Gonzalez-Navarro (2018) estimate the effects of the entry of multinationals. Bao and Chen (2018) use firm-specific measures of foreign competition threat to show that domestic firms respond by upgrading productivity, raising innovation, and altering product composition. Atkin, Faber and Gonzalez-Navarro (2018) estimate the effect of foreign supermarket entry in Mexico on household welfare and find that foreign entry causes large welfare gains (particularly for higher-income households). These gains occur through price reductions at domestic stores and direct consumer gains from foreign stores.

The second stream of literature this paper relates to is barriers to small-firm growth in developing countries. Karlan, Knight and Udry (2015), Bruhn, Karlan and Schoar (2018), Bloom et al. (2012), and McKenzie and Woodruff (2017) study the role of consulting services and management practices, Alfaro-Urena, Manelici and Vasquez (2019) and Atkin, Khandelwal and Osman (2017) study access to international buyers, Atkin et al. (2017) study technology adoption, and De Mel, McKenzie and Woodruff (2008) and Fafchamps et al. (2014) study access to finance and capital. The heterogeneous effects of competition from chains on shops highlight an understudied trade-off for small firm growth. On the one hand, when shops grow, they may access more customers and exploit economies of scale. On the other hand, they might lose comparative advantages from being small and owner-operated, differentiating them from large chains and allowing them to survive.

The following section provides background information on shops, chains, and competition. In Section 3, I describe the data sources and document that chains have regional economies of scale and are more than three times as likely to open on wide streets. Section 4 presents the empirical strategy and discusses potential

[4] In developed countries, the literature on entry and competition initiated by Bresnahan and Reiss (1991, 1990) is more extensive. This paper is most closely related to prior work that has studied the effects of increased competition in retail markets and the expansion of Walmart in the United States (Jia (2008); Matsa (2011); Basker (2005); Basker and Noel (2009); Hausman and Leibtag (2007); Holmes (2011); Haltiwanger, Jarmin and Krizan (2010)).

concerns about the instrument's validity. In Section 5, I present the main results. In Section 6, I discuss why shops survive using a discrete choice model and the heterogeneity of the effect on shops. This section also presents the welfare estimation results across the income distribution. Section 7 includes ample robustness checks for alternative instrument specifications, including sets of controls and alternative standard errors. The last section concludes.

2 Background

One of 10 firms and one of four retail firms in Mexico is a neighborhood shop. They are, on average, 28 square meters, employ 1.7 people (mostly owner and family), and are primarily located next to the owners' houses (Economic Census, 2019). Shops use different sourcing channels to offer a wide variety of products. Large producers directly deliver packed, branded, and standardized products such as bread, dairy, cold meats, sodas, beer, and snacks to shops. Shop owners source fresh fruit and vegetables from central markets known as *centrales de abasto* and offer products that they make themselves (e.g., bread, sandwiches, pastries) or source from nearby bakeries and *tortillerias*. Shops in Mexico are often perceived as more than just a store:

> For most consumers in Mexico, shops are much more than a purchase location ... they are places where it's possible to find what we need because the owner knows us to perfection. The owners' relationships with the people make them a central link of the community ... [the shops] have also been, since always, the meeting place of neighborhoods. ... In them, we learn about solidarity, personal finance, and trust in one's word.
>
> Coca-Cola Mexico (2020)

Oxxo, 7-Eleven, Circle K, 3B, Dunosusa, and Tiendas Neto are the most prominent chains rapidly expanding in the last two decades, reaching more than 22,000 stores in 2019. Chain stores are between 20 and 50 square meters plus parking, employ between 6 and 10 people, and stock between 300 and 800 SKUs. Even though chains and shops are often within a few meters, chains are in high-traffic locations next to wide streets (Milenio, 2016; El Universal, 2015). Chains are perceived as very successful. In particular, the largest of them, OXXO, is perceived as the country's most successful food and beverages retailer, surpassing Walmart Mexico (El Financiero, 2014). OXXO's annual sales per square meter are 89,500 MXN, exceeding Walmart Mexico's 88,800 MXN, and OXXO's EBITDA margin, a measure of operating profitability, is 11.2%, larger than that of all supermarkets in Mexico, including Walmart, with an EBITDA margin of 9.3% (El Financiero, 2020).

There are several reasons for the rapid expansion of convenience chains in Mexico. On the one hand, OXXO and Extra owners were the two largest beer companies, Cuauhtemoc-Moctezuma and Grupo Modelo, and convenience chains allowed them to bring their products closer to consumers. Additionally, Cuautemoc-Moctezuma and OXXO's owner, is the world's largest beverage bottler and marketer of the Coca-Cola System by sales volume (FEMSA, 2023), making OXXOs strategic for distributing both beer and beverages. Different from OXXO and Extra, 7-Eleven, a joint venture between Casa Chapa and the Southland Corporation, boasted of offering variety to their consumers, having Coca-Cola and Pepsi products and Corona and Tecate beers. Another potential stimulus of the expansion of chains was the North American Free Trade Agreement, which increased access of Mexican firms to global financial markets and allowed for more and stronger joint ventures with American firms.

The convenience chain industry has experienced important changes, and chains have become relevant as a profitable standalone business. Heineken bought the beer-making operations of FEMSA (Cuauhtemoc) in 2010 (BBC, 2010), and Circle-K bought all the Extra stores in 2014 (El Financiero, 2014). In 2021, the revenue of OXXO's surpassed that of Coca-Cola FEMSA (FEMSA, 2021), and in 2023 FEMSA announced reducing its holding in Heineken from 15% to 8% ($3.4 billion USD transaction) to reignite growth, with the expectation that the retail operation, largely comprised of OXXO, will contribute more than two-thirds of the firm's future revenue and profits (Reuters, 2023).

Even though large producers like Coca-Cola, Pepsi, and beer companies deliver their products directly to both chains and shops, a key to chains' success is their in-house logistics operations with distribution centers around the country that facilitate the distribution of goods to each store (El Financiero, 2014). For example, OXXO, as of 2021, had 21 regional distribution hubs that source half of the products that the chain sells (OpporTimes, 2021). Smaller chains operate similarly; Tiendas 3B, with around one thousand stores, relies on 10 distribution hubs to distribute the products they sell to each store (Tiendas 3B, 2023). Having their own distribution centers has also allowed chains to promote sales of their own brands. For example, 7-Eleven has *Café Select*, *Fresh Food*, and *Big Bite*, OXXO has over 25 store brands, including *Andatti*, *Vikingo*, *Del Marqués*, and *Festivo*, and 3B also has over 10 store brands, including *Vaca Blanca*, *Mayorela*, *Lactibu*, and *Nuestro Campo*.

Chains are direct competitors to shops because they are similar in size, capture incidental purchases of consumers, and have a significant overlap in their product offerings. Additionally, chains may represent an existential threat to shops because they have advantages in scale that allow them to share costs across stores, have more bargaining power with suppliers, lower capital costs, and invest in productivity-enhancing technologies. Chains also represent lower search costs to consumers because they have uniformity across same-chain stores, are located on wide streets, have big signs, and operate 24/7. According to government officials, chambers of commerce, and market research companies, between 5 and 35 shops close for each additional chain store (El Universal, 2017; El Universal, 2015; El Financiero, 2018). While the magnitude is unknown, it is likely that the number of shops will decline. However, the decline could be driven by a reduction in the number of entries or an increase in exits. While the expected effect on entries is an unambiguous decline, the number of exits could actually decrease if there are fewer shops (due to fewer entries).

However, chains could have a limited effect on shops because shops may have comparative advantages in building relationships with consumers, tailoring their product offerings, offering informal credit to the neighbors, and providing similar prices (Gonzalez Sanchez and Gaytán (2015); Milenio, 2016). Moreover, consumers are likely to buy less in shops, but because there are also fewer shops, the effect on sales and profits on surviving shops is ambiguous. The model of differentiated competition in the Online Appendix B formalizes the mechanisms that would lead to the reduction in the number of shops driven by a decline in entries, but not increased exits, and the negative effects on shops concentrating on the extensive margin but being much smaller for surviving shops.

3 Data

A. Sources

The three primary data sources are: i) Economic Censuses (1999, 2004, 2009, 2014, 2019) collected by the Mexican Statistics Institute (INEGI), ii) Income and Expenditure Surveys (2006, 2008, 2010, 2012, 2014, 2016, 2018) collected by INEGI, and iii) Open Street Maps.

The Mexican Economic Censuses cover all the firms in the country without any restriction,[5] and the confidential part includes microdata on, among other variables, revenue, profits, employment, investment, operations, and location. The Economic Censuses classify the establishments according to the North America Industrial Classification System for Mexico (SCIAN), which has subtle differences that represent a significant advantage relative to the North America Industrial Classification System for the United States (NAICS). Unlike the NAICS, with a code for supermarkets (445110) and one for both convenience stores and shops (445120), in the SCIAN classification, shops, chains, and supermarkets have different codes, 461110, 462112, and 462111, respectively. I further classify establishments with the 462112 code, composed of convenience stores (mini-markets), into two categories based on ownership: firms with more than 100 establishments as chains and those with only one store as hybrid stores. In number, hybrid stores are equivalent to 3% of neighborhood shops and convenience chains. I do not include hybrid stores in the analysis, except when comparing the effect of chains on shops and hybrid stores in the Discussion section.

Starting in 2009, INEGI added an establishment identifier to the Economic Censuses. To track establishments before 2009, I use the establishment identifiers created by Busso, Fentanes and Levy (2018). The result is an establishment-level panel from 1999 to 2019.

The biyearly Income and Expenditure Surveys (ENIGH) of 2006-2018 contain data on what households buy, where they buy it, and how they pay. The sample of the ENIGH has grown throughout the years. In 2006, it contained responses from little more than twenty thousand households; by 2018 it included more than seventy thousand responses.

INEGI's geostatistical framework for urban Mexico divides the country into states, municipalities, localities, and urban census tracts (AGEBs). The data include between 37,000 and 47,000 AGEBs (depending on the census year) with an average size of between 25 and 50 blocks, 650 households, and 2,000 people. AGEBs are perfectly delimited by streets, avenues, or any other trait easily identifiable in the field. INEGI designed the AGEBs to facilitate the data recollection process by enumerators in the field.

I use AGEBs to construct neighborhoods. Drawing a buffer of 1km from the center of each AGEB, I define a neighborhood as the union of AGEBs that overlap with each buffer.[6] On average, there are 12 AGEBs in each neighborhood, 370 blocks, 30,000 people, 68 shops, and five chain stores. The robustness section includes results using alternative buffer sizes (0km, 0.25km, 0.5km, 0.75km, 1.25km, 1.5km, and 2km). There are two reasons for using a buffer larger than 0km (running the analysis at the AGEB level). The first is statistical power, which is only an issue when using ENIGH data. Using neighborhood fixed effects limits the sample to neighborhoods where households were interviewed by the ENIGH at least two times. The larger the neighborhood size, the more neighborhoods meet this condition. The second reason is to ensure that the neighborhood is large enough to capture the effect on all the shops affected by the entry of a chain store so that spillovers to other neighborhoods do not bias the estimates. Figure A.4 displays the frequency distribution of neighborhoods by the number of chain stores and shops.

Based on the Open Street Maps street classification, I re-classify trunk, primary, secondary, and tertiary streets as *wide* and the remaining categories as *not wide*. In the resulting classification, 21% of the total street length is *wide*, and of the remaining 79% of *non-wide*, 95% are residential streets. I construct a measure of the prevalence of wide streets by adding the lengths of all wide streets in the neighborhood and normalizing it by their size, specifically dividing by the square root of their area. This measure ranges from 0 to 63 (less than 1% of neighborhoods have 0), the average is 10, and the standard deviation is 7.6.

[5] They include both formal and informal firms without minimum size requirements.

[6] Figure A.5 has a visual representation of how neighborhoods are constructed.

I use the Population Censuses of 2000 and 2010 for i) alternative specifications that use machine learning to construct a measure of suitability for chains instead of using the availability of wide streets and ii) for specifications that use population census data as controls. I present the results for these specifications in the Robustness section.

I use the price microdata INEGI uses to construct the inflation index. These data contain bi-weekly prices of products at the bar-code level. While these data are very rich to study changes in prices within an establishment across time, price comparisons of the same product across establishments are often underpowered because enumerators at each establishment surveyed define the exact product within a product category for which the price is going to be recorded biweekly (INEGI, 2018). Hence, to compare prices across two establishments, enumerators at each establishment must have chosen the same product within the product category (e.g., the price comparison between two establishments is possible if enumerators chose Coca-Cola of 600 ml in both locations, but not if on one they chose Coca-Cola of 600ml and in the other Coca-Cola of 1lt or any other soda).

After merging the different data sources, the sample includes the most populous 655 municipalities in Mexico, with an average population of 115,000. The distribution of these cities by size is i) small: 508 towns with an average population of 37,000, ii) medium: 120 towns with an average population of 262,000, and iii) large: 29 towns with an average population of 880,000.

B. Summary Statistics

Table 1: Summary Statistics Shops and Chains

	Shops	Chain Stores
Number	2,061,389	46,659
Annual Profits (000's MXN)	70	1,763
Annual Revenue (000's MXN)	261	10,233
Expenses (000's MXN)	190	8,522
Value Added (000's MXN)	72	2,108
Total Employed	1.8	6.4
Profits per Worker (000's MXN)	41	332
Revenue per Worker (000's MXN)	152	2,079
Initial Resale Inventory (000's MXN)	11	528
Final Resale Inventory (000's MXN)	12	686
Fixed Assets (000's MXN)	68	2,121
Publicity (000's MXN)	0.1	34
HH Purchase Probability (Week)	0.85	0.16
HH Purchase Probability | Purchasing in Chain (Week)	0.68	1
HH Number of Days Visited per Week	4.00	0.30

Source: Economic Censuses and Income and Expenditure Surveys

There are stark differences between shops and chains. On average, chain stores have 40 times the revenue, 25 times the profits, 2 times the employees, 15 times the profits per employee, and 25 times the revenue per employee. Chains are 2-5 times larger in square meters than shops (4-10 times, including parking), yet this difference in physical size is not enough to explain the differences in profits and revenue.[7] While 85 percent of households purchase at least once a week in shops, the probability of buying in a chain is significantly lower, 16%. However, for households who purchase in chains, the likelihood of purchasing in shops is 17 percentage points lower than for the average household, consistent with these two types of establishments being substitutes. Shops' exit rate from one census to the next is 40%, implying a 10% annual exit rate, which is similar to the exit rate is similar to the 8.3% average exit rate of microenterprises in other developing countries (McKenzie and Paffhausen, 2019). For chains, the yearly exit rate is below 3%.

Shops and chains have a significant overlap in their product offering. The five most popular products for shops (sodas, milk, eggs, tortillas, and bread), which represent almost half of their revenue, are also available and are among the 12 most popular food products in chains (Figure A.2). A limitation of the consumption data is that they do not include information on quality or brand, which makes price comparisons between chains and shops inconclusive. To partially address unobservable differences in quality, I control using household fixed effects when comparing prices paid in shops and chains. Figure A.13 presents the estimates of the difference in the price paid and the size purchased in chains vs. shops. The differences in prices and dimensions are not statistically significant for most goods. For goods with a difference in price, volume (size) discounts are likely driving the difference. For example, sodas are cheaper per liter in shops, but households also purchase larger sizes in shops. Similarly, rice is more expensive per kg in shops, but households purchase smaller bags of rice in shops. Table A.4 presents the average price differences between chains and shops using ENIGH and Price microdata. The disadvantages of ENIGH are that it does not include product size for non-food items (e.g., there is no information on whether the shampoo purchased is 1 liter or 250 ml), and products are broadly defined (e.g., sodas, but no brand or flavor). The price microdata provide prices at the bar-code level, but there is little overlap between the exact bar-code selected to record prices from convenience chains and neighborhood shops. To guarantee enough overlap, the comparisons using the price microdata are within the city and not within the census tract. Hence, chain prices may be higher because chains are more likely to be located in more expensive areas of the city, and there is not enough data to compare their price to that of shops in the same area. Based on the ENIGH, chains are 4% more expensive in food and 1% more expensive in non-food, but the latter is not statistically significant. Based on price microdata, chains are 15% more expensive in food and 14% cheaper in non-food.

C. Importance of Economies of Scale and Wide Streets for Chains

I use two key differences between chains and shops to construct the instrument. The first is that chains enjoy advantages from opening stores in nearby cities. Some of these advantages are cost-sharing in transportation, marketing, distribution, and overhead costs that generate regional economies of scale. Other potential benefits include specialization and brand building. If these advantages of opening in nearby cities are significant, chains will open stores in cities close to each other to exploit them. The map in Figure 1 shows that chains' store openings between 2016 and 2020 present a spatial correlation consistent with the advantages of opening stores in nearby cities.

Online Appendix C quantifies the relevance of these advantages in determining the number of stores each chain has in a city. In particular, after controlling with firm-city, year-city, and year-firm fixed effects, 18 additional same-chain stores in nearby cities (cities adjacent to this city and those adjacent to it) are associated with one more store in the city. Stores in nearby cities account for 9% of the total variation in

[7] Chain stores are, on average, 187 square meters or 420 square meters, including parking, while shops are between 40 and 100 square meters.

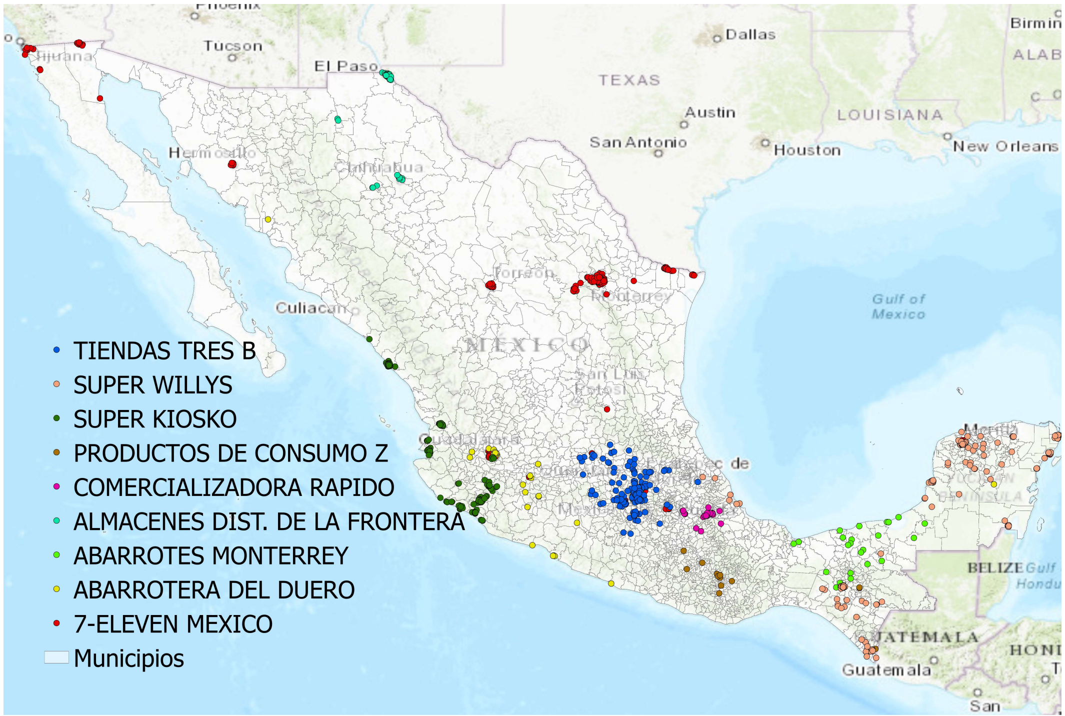


Figure 1: Spatial Correlation in Store Openings by Chain (2016-2020)

Note: The map plots chains' openings between 2016 and 2020 by chain using data from DENUE 2020. Only nine of the largest 20 chains by number of stores in the country are used in the map for exposition purposes.

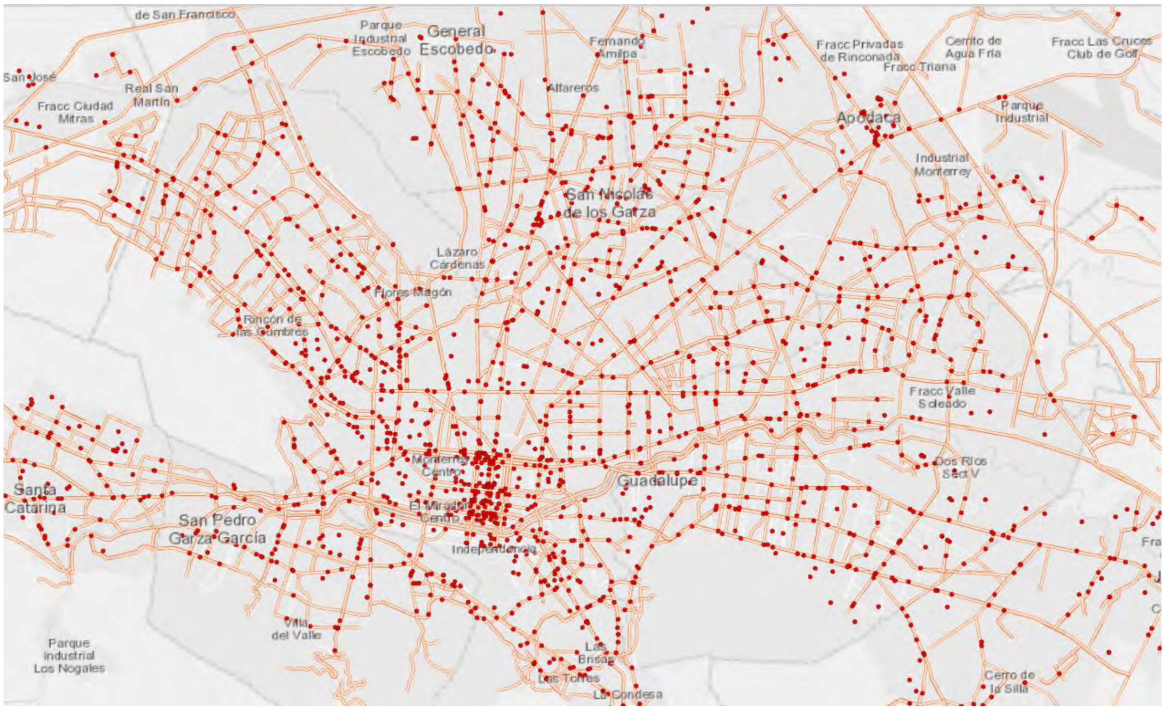
the number of stores each chain has in a city.[8] These advantages of opening stores in nearby cities are firm-specific: the positive correlation dissipates when using the number of different-chain stores (competitors) in cities nearby. Moreover, the number of competitors in nearby cities accounts for less than 0.001% of the variation in the number of stores each chain has in a city.

The second key difference is that even though shops and chains coexist a couple of meters away, shops are usually next to the owners' houses, and chains are next to wide streets to target car-driving and bus-riding customers. Chains also display big signs, offer parking spots, and provide a speedy process to enter, purchase, and leave. If traffic customers are essential for chains, they will mainly locate on wider streets to target them. The map on the top of Figure 2 shows that chains are almost exclusively situated on wide streets, and the bottom map shows this is not the case for shops. More formally, Figure A.6 displays the distribution of distance from each store to the closest wide street. Almost 80% of chain stores are within 25 meters of a wide street, while only 20% of shops are this close to a wide street.

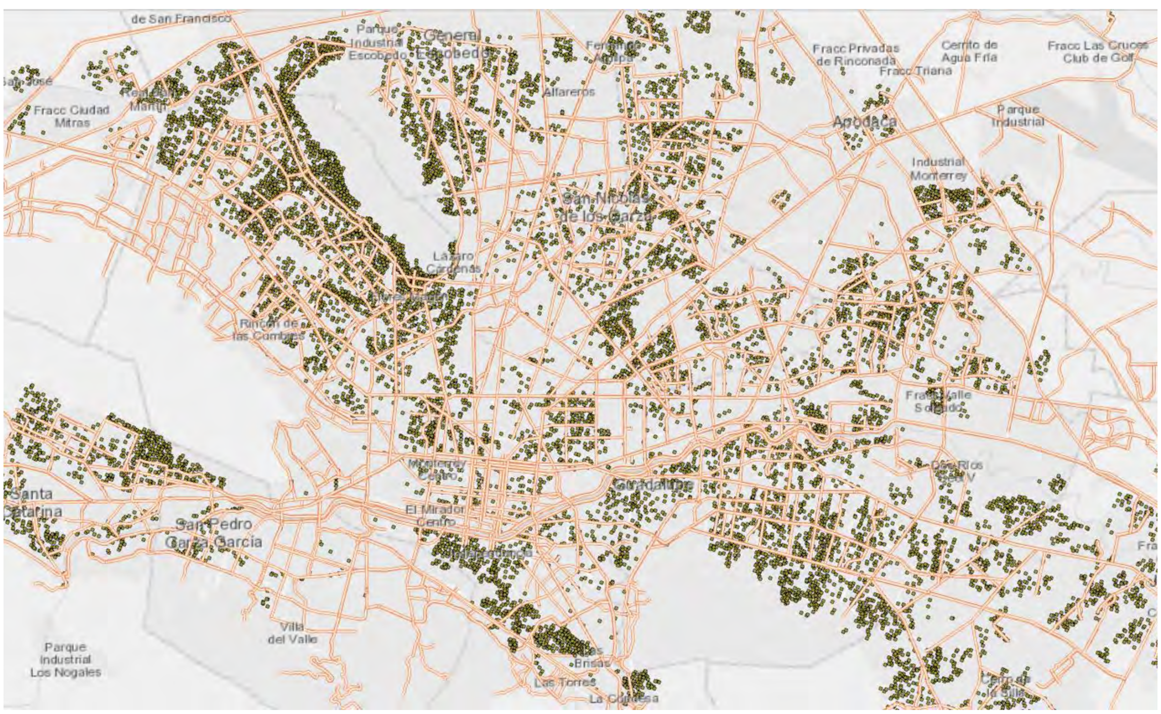
4 Empirical Strategy

Chains' entry time and location across cities and within cities (across neighborhoods) are endogenous to shops' outcomes. The endogeneity arises from joint determination: neighborhoods with higher demand for products offered by both store types have better outcomes for shops and are more attractive for chains. This positive correlation in demand leads to an upward bias of the effects of chains on shops if estimated using

[8]The 9% is the R-squared of the model after demeaning by all the fixed effects. If the specification only uses adjacent cities, the estimate is larger. Nine additional same-chain stores in neighboring cities are associated with one more store in the city.



Wide Streets and Chains



Wide Streets and Shops

Figure 2: Wide Streets, Chains, Shops of Monterrey

Source: Open Street Maps, DENUE 2020
Note: The maps plot wide streets and chain stores or shops. Wide streets are those classified as Trunk, Primary, Secondary, and Tertiary on Open Street Maps.

OLS.

I control for time-invariant neighborhood characteristics and city-wide trends using city-year and neighborhood fixed effects. However, fixed effects do not control for neighborhood-level unobservable shocks. For example, a new park may increase foot traffic and demand for drinks and snacks for both store formats. If I compare neighborhoods where chains enter to those where they do not, I would implicitly compare neighborhoods that received positive demand shocks for shops to those that did not. To address this issue, I use an instrument that reduces the costs and increases the profitability of chains, but not of shops.

As shown in equation 1, the instrument uses an interaction to exploit two key differences between chains and shops: i) chains have regional economies of scale,[9] and ii) chains locate on wide streets. The left side of the interaction is a Herfindahl–Hirschman Index without normalization that measures regional economies of scale and increases in the number of chain stores in nearby towns (excluding those in this town) and their concentration. Specifically, it is the square root of the sum of the squared number of stores per chain in nearby cities.[10] I use the lagged number of chain stores in nearby cities to avoid simultaneity issues potentially arising from the contemporaneous number of chain stores in the city influencing the number of chain stores in nearby cities. Nearby cities are those adjacent to the city and cities adjacent to those (1^{st} and 2^{nd} degree neighbors).[11] Instead of a measure of regional advantages that aggregates across firms, it is possible to use one measure and one instrument for each chain. The robustness section shows that the results are almost identical when using one measure and one instrument per chain. Still, the main specification has the advantage of a stronger first stage and allows for more transparent heterogeneity analysis and placebo checks due to only using one instrument. In summary, to predict the increase in chain stores in a neighborhood, the regional economies of scale measure uses the previous increase in the number of chain stores in neighboring cities.

The economies of scale measure provides variation at the city and year level, but it does not predict where, within cities, new chain stores will locate. Since the catchment areas of chains and shops are much smaller than entire cities, it is critical to have variation within cities to estimate the causal effect of chains on shops. Moreover, while additional same-chain stores in nearby cities would make all neighborhoods in this city more profitable, many of these neighborhoods would still not be (and might never be) profitable or suitable enough for the chain to enter. Hence, accounting for a neighborhood's suitability for chains will strengthen the instrument's first stage. To predict the location within cities, I construct a measure of suitability for chains at the neighborhood level based on the prevalence of wide streets, which is the right side of the interaction in equation 1. The measure of suitability for chains is the total length of wide streets divided by the square root of the neighborhood area.[12] The instrument is the interaction of the regional advantages and suitability measures. It captures that when chains open stores in nearby cities, suitable locations in this city become more attractive for chains. The instrument only uses variation from the interaction of the measures; two-way fixed effects absorb the individual components.

[9] Jia (2008) and Holmes (2011) have used this intuition to model the expansion of Walmart in the United States.

[10] In the Robustness section, I repeat the estimation, but i) without squaring the number of chain stores and without taking the square root, and ii) without taking the square root. The main specification has the advantage of having a conceptual link to the Herfindahl–Hirschman index and a stronger first stage.

[11] The robustness section includes results using 1^{st} and up to 3^{rd} degree neighbors

[12] I use the square root of the area so that the numerator and denominator units are in meters. Neighborhoods have different sizes because they are unions of census tracts.

$$Z_{n,c,t} = \underbrace{\left(\sum_{f} (\#StoresNearbyTowns_{f,c,t-1})^2\right)^{1/2}}_{\text{Economies of Scale}_{c,t}} \times \underbrace{\frac{Total\ wide\ streets\ length_{n,c}}{Area_{n,c}^{1/2}}}_{\text{Prevalence of Wide Streets}_{n,c}} \tag{1}$$

Equations 2 and 3 are the first and second stages of the 2SLS estimation.

$$CS_{nct} = \gamma_1 Z_{nct} + \zeta_{nc} + \eta_{ct} + \sigma X_{nct} + \mu_{nct} \tag{2}$$

$$Y_{nct} = \beta_1 \widehat{CS}_{nct} + \zeta_{nc} + \eta_{ct} + \sigma X_{nct} + \epsilon_{nct} \tag{3}$$

where n denotes neighborhood, c denotes city, t denotes census year, and f denotes firm. Y_{nct} is the outcome of interest, e.g., number of shops, revenues, profits, neighbors' expenditure in shops, prices, etc. CS stands for the number of chain stores. The estimation includes neighborhood fixed effects, ζ_{nc}, city-year fixed effects, η_{ct}, and economic activity controls, X_{nct}. The economic activity controls are the seven factors with an eigenvalue larger than one from a factor analysis. The factor analysis reduces the dimensionality of the number of establishments for each SCIAN retail classification (six digits, 84 classifications in total), e.g., butchers, ice cream shops, shoe stores, bookstores, and pet stores. The retail establishments in the SCIAN have a code starting with 46, equivalent to code 44-45 for the NAICS for the US and Canada. I cluster the standard errors at the city level because the measure of advantages from the regional expansion of chains varies at the city level.[13]

The instrument validity relies on the exclusion restriction. This restriction is that when chains increase the number of stores in nearby cities, it only affects shops in neighborhoods suitable for chains by increasing the probability of a chain entering their neighborhood. If there were factors affecting the entry of chains in nearby cities and the economic outcomes of shops in neighborhoods that are suitable for chain stores, the instrument would be invalid because the estimated effect of the entry of chains would also include the effect through these factors. The next paragraphs discuss specific possible violations of the exclusion restriction and how they are addressed.

A possible violation of the exclusion restriction is that regions with economic booms will have more entries of chains and will also be more profitable for shops. City-year fixed effects control for these city-wide trends. However, economic booms in the region would still be an issue if they resulted in more chains in neighborhoods with more wide streets and if these neighborhoods were the ones where household income grew the fastest. In particular, the problem would be that the instrument would be correlated with household income, hence with demand faced by shops, violating the exclusion restriction. This concern is addressed in multiple ways. First, I include economic activity controls in the main specification. Second, I show that it is not a city-level variation that drives chain entry but a firm-level variation. If city-wide trends were driving chains' entry, we would expect several or all chains to enter the same cities simultaneously. This is not the case. Online Appendix C shows that additional same-chain stores in nearby cities predict the number of stores of the chain in this city (explain 11% of the variation); nonetheless, competitors' stores in nearby cities do not predict the number of stores in this city. The regional economies of scale are firm-specific.

[13]The robustness section includes estimates clustering at the neighborhood, city and year, city x year, and city x year and neighborhood levels. It also presents standard errors accounting for the potential correlation of errors across adjacent cities and neighborhoods.

Third, since it is impossible to directly test whether the instrument affects shops through mechanisms other than the entry of chains, I test whether the instrument correlates with household characteristics that likely affect the demand shops face. Figure A.8 shows no correlation between the instrument and household characteristics, such as the number of cars, the probability of having a vehicle, labor income, total income, income per capita, monetary expenses, and household demographics. This exercise provides reassurance that mechanisms associated with these variables or correlated with these variables do not represent a violation of the exclusion restriction. And fourth, Table A.1 shows that while the instrument is correlated with the number of neighborhoods shops and convenience chains, it is not correlated with the number of other retail establishments, e.g. supermarkets, department stores, butchers, fruit and vegetable stores, wine and spirits, and beer stores.

A related concern is that consumers might purchase in chain stores outside their neighborhood, leading to spillover effects where the chain affects both consumers and shops in the neighborhood of entry and adjacent ones. To address this concern, I re-estimate the main specification using eight alternative neighborhood sizes in 250 meters increments of buffer radius. As Figure A.11 shows, the effect on the number of shops is similar using buffers between 0.25km and 2km, consistent with the neighborhood size of the main specification being large enough to capture the full effect of an additional chain store.

An additional concern on the empirical strategy might be that there is not enough variation in the data after considering the city-year and neighborhood fixed effects. Figure A.12 shows plenty of variation in the first stage and the reduced form, even after residualizing by city-year and neighborhood. Regarding the monotonicity of the instrument, A.7 shows that the relationship between the instrument and the number of chains monotonically increases by plotting the relationship between the number of chains and dummies for each decile of the instrument.

5 Results

The first part of this section estimates the effects of chains on shops, including the impact on the number of shops, number of entries, number of exits, and performance measures like revenue, profits, and employment at the neighborhood and shop level. The second part presents the effects on neighbors' consumption, including expenses on shops, number of visits to shops, probability of visiting shops, expenses by product category, and expenses by product.

A. Effects of Chains on Shops

For each additional chain store in the neighborhood, the number of shops decreases by 3.85. An expansion from zero to the average number of chain stores in a neighborhood, 6.7, reduces the number of shops by 26 (15%).[14] Column 4 in Table 2 contains the second stage results of the main specification (equation 3). Column 1 is an OLS estimation without fixed effects, where the joint determination problem is evident. Markets with higher demand have both more chain stores and more shops. In Columns 2 and 3, I partially address the issue by introducing year-city fixed effects and economic activity controls. In Column 4, I further address it by introducing year-city fixed effects. However, the effect in Column 4 still suffers from an upward bias due to neighborhood-level demand shocks that are common for both store formats. I address this bias in Column 5, which presents the 2SLS estimates using the instrument. Columns 6 and 7 report the reduced form and first-stage estimates.

[14] Conditional on having chain stores, neighborhoods have, on average, 6.7 chain stores and 175 shops.

Table 2: Effect of Chains on the Number of Shops

	OLS				2SLS	Reduced Form	First Stage
Dependent Variable: # of Neighborhood Shops	# of Shops	# of Shops	# of Shops	# of Shops	# of Shops	# of Shops	# of Ch.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Number of Chain Stores	3.26***	2.17***	-0.15	-1.65***	-3.85***		
	(0.542)	(0.811)	(0.367)	(0.248)	(0.758)		
Economies of Scale$_{c,t-1}$ x Chain Suitability$_{m,c}$						-5.09***	1.32***
						(0.796)	(0.169)
Observations	158,515	158,515	158,515	158,515	158,515	158,515	158,515
Year x City FE		Y	Y	Y	Y	Y	Y
Economic Activity Controls			Y	Y	Y	Y	Y
Neighborhood FE				Y	Y	Y	Y
Clustered SE	City	City	City	City	City	City	City
Mean Dep. Variable | Chains>0	175	175	175	175	175	175	7
Mean Chain Stores | Chains>0	6.7	6.7	6.7	6.7	6.7	6.7	6.7
KP F-statistic					61.18		

Note: The table displays the estimation of Equation 3 using 2SLS. Columns 1-4 are OLS estimates (use the number of chain stores as independent variables), and column 5 is the IV estimate. Columns 6 and 7 are the reduced form and the first-stage estimates. Standard errors are clustered at the city level. The 2SLS estimations are based on Correia (2018).

The reduction in entries is the primary driver of the decrease in the number of shops. For each additional chain store, the number of shop entries decreases by 1.4, and the number of exits decreases by 0.7. These estimates imply that an expansion from zero to the average number of chain stores in a neighborhood reduces entries by 14% and exits by 7%. These results are columns 1 and 2 of Table 3. The reduction in exits might appear surprising at first. However, the effect of chains on the number of shop exits is ex ante ambiguous because the decrease in entries may also reduce exits because there are now fewer shops.

Table 3: Effect of Chains on Number of Entries and Exits

Dependent Variable:	Number of Entries	Number of Exits	Entry Rate	Exit Rate
	(1)	(2)	(3)	(4)
Number of Chain Stores	-1.39**	-0.68**	-0.002**	0.004***
	(0.689)	(0.328)	(0.001)	(0.001)
Observations	155,800	155,800	155,719	155,666
Economic Activity Controls	Y	Y	Y	Y
Neighborhood FE	Y	Y	Y	Y
Year x City FE	Y	Y	Y	Y
Mean Dep. Variable | Chains>0	66	69	0.38	0.41
Mean Chain Stores | Chains>0	6.7	6.7	6.7	6.7
KP F-statistic	60.24	60.24	60.15	60.20

Note: The table displays the estimation of equation 3 using 2SLS. Standard errors are clustered at the city level.

I also estimate the effect on entry and exit rates and report the results in Columns 3 and 4. Ideally, the entry rate would capture the number of entrants among the potential entrants. I cannot construct this rate because the number of potential entrants is unknown. Instead, I use the ratio of new shops to existing shops. Chains reduce the number of shops in the neighborhood, implying that the entry and exit rates will change through the numerator and the denominator. An expansion from zero to the average number of chain stores in a neighborhood reduces the entry rate by 1.3 pp (3.5%) and increases the exit rate by 2.7 pp (6.5%). I also estimate the effect on the probability of exit using survival models: Cox, Poisson, and Linear with different combinations of fixed effects and store-level controls. Going from zero to the average number of chains in a census tract implies an increase in the exit probability of shops between 2.6 and 4.5 pp (Columns 5 and 6 of Table A.2).

Figure 3 shows that the negative effects on shops concentrate on the extensive margin. An expansion from zero to the average number of chain stores in a neighborhood reduces industry (neighborhood) level revenue and profits for shops by 29%. There are similar effects for resale revenue, value-added, profits per worker, and inventories. These include the effects on shops that remain open and those that closed or did not open. The shop level effects are around 1/3 of the industry impact–the average profits and revenue of shops decline by 10%, consistent with the reduction in the number of shops mitigating the negative effects of chains' expansion at the shop level.

Interestingly, there is no effect on productivity (measured as output-input ratio), hours worked, total employed, and hours per worker at the shop level. These results might appear conflicting because there is no change in the output-input ratio even though shops have lower revenue and unchanged labor input. However, the measure of inputs is an accounting measure, meaning it does not capture the owner's opportunity cost (its potential salary). Hence, shops adjusting to lower revenues by decreasing purchases of goods for resale is driving the null effect on productivity measured by the output-input ratio. Shops also reduce their inventory holdings, a rational response from a sophisticated manager concerned about performance metrics such as inventory turnover.

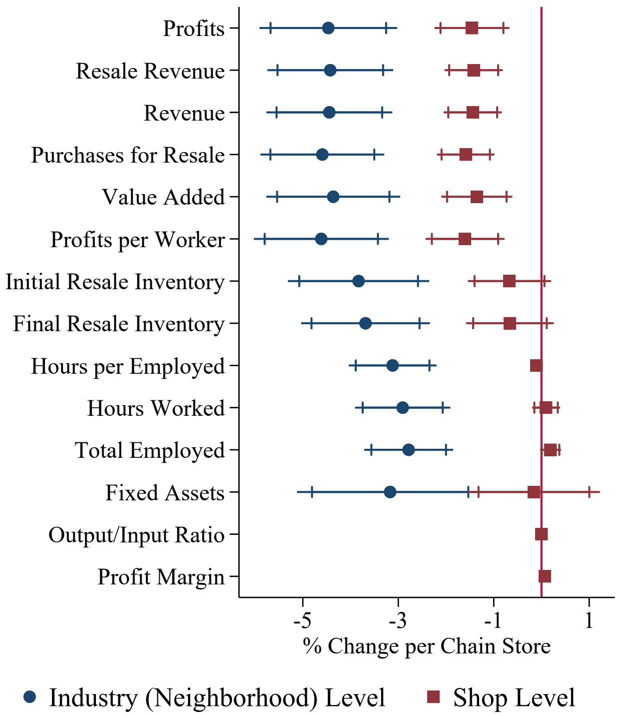


Figure 3: Effects on Shops' Performance

Note: The figure displays the estimation and the 90 and 95% confidence intervals of Equation 3 using 2SLS where the dependent variable is the inverse hyperbolic sine of the sum or average variable in the row. Standard errors are clustered at the city level.

Regarding prices, shops could have lowered prices to prevent a loss in market share or raised them to boost profitability since they are now selling to consumers who may be, on average, more inelastic. However, I do not find a significant effect on shops' prices using price data from ENIGH and the price microdata (Table A.6). Two potential explanations are that convenience chains compete in amenities instead of prices and that shops are price takers. Moreover, manufacturer-suggested prices may be closer to a mandate than a suggestion. The largest producers provide lists with retail prices to shops and sometimes include the prices in the packaging or the in-store promotional ads, giving shops little flexibility to adjust prices (Expansion, 2022; Cardamomo, 2022; Milenio, 2022).

Regarding the effect on employment and wages, an additional chain store in the neighborhood reduces the number of jobs in shops by almost 7 because it reduces the number of shops by 3.85, and each of them, on average, had 1.8 workers (including owners). However, this job reduction should probably cancel out with increased jobs at convenience chains. Consistently, Table A.5 shows that each additional chain store in the neighborhood increases the number of jobs in the chain and shop segment by 1.7, but the estimate is not statistically significant and relatively small (less than 0.5% of the employment in the segment). However, focusing only on jobs and excluding owners, each additional chain store in the neighborhood increases the number of jobs in the chain and shop segment by 7.43. Regarding the effect on wages, the expansion of chains has no effect on the wages paid to shop employees. However, because chains pay more than shops to their employees, each additional chain store increases the average wage in the segment (shops + chains) by 1%.

B. Effects of Chains on Neighbors' Consumption

Table 4 shows that most households continue to purchase in shops but frequent them less and spend less. An expansion of chain stores from zero to their average number in the neighborhood decreases the probability of neighbors purchasing in shops by -3.5%, and equivalently, shops retain 96.5% of their customers. However, the average number of days neighbors visit shops declined by 8.5%, and the expenditure in shops declined by 10%. The 12% reduction in food purchases, shops' top-selling category (90% of sales), accounts for the entire decline in shop purchases. Moreover, there is no decline in fresh food purchases, while non-fresh food purchases decline by 15%.

Table 4: Effect of Chains on Neighbors' Consumption

	I[Purchase]	Weekly Visits	Expenses ($)	Food ($)	Fresh Food ($)	Non-Fresh Food ($)
	(1)	(2)	(3)	(4)	(5)	(6)
Number of Chain Stores	-0.003	-0.034*	-27.41*	-28.96*	-0.15	-27.59**
	(0.002)	(0.019)	(16.62)	(15.69)	(1.41)	(13.14)
Observations	987,689	987,689	987,689	987,689	983,563	983,563
Economic Activity Controls	Y	Y	Y	Y	Y	Y
Year x City FE	Y	Y	Y	Y	Y	Y
Neighborhood FE	Y	Y	Y	Y	Y	Y
Avg. Dep. Var.|Chains>0	0.86	3.9	2,559	2,306	293	1,790
0 to Avg. # Chain Stores	-3.5%	-8.5%	-10.4%	-12.2%	-0.5%	-14.8%
KP F-Statistic	85.72	85.72	85.72	85.72	85.44	85.44

Note: The table displays the estimation of equation 3 using 2SLS. Standard errors are clustered at the city level. Expenses are in Mexican Pesos (MXN).

Figure 4 displays the stark difference in the effect of chains on neighbors' consumption of non-fresh and fresh products. While losing sales in non-fresh and packed products like sodas, milk, cigarettes, cookies, and juices, shops retain sales of fresh products like fresh pastries, tomatoes, fresh bread, potatoes, onions, and avocados. The purchase reduction for products with fresh and non-fresh variations is only for their non-fresh version. Such is the case of packed pastries and cookies, for which sales decline, while sales for fresh pastries and fresh bread do not change. Another example is spicy food. On the one hand, neighbors purchase less packed chilies and salsa from shops, but on the other, they keep buying serrano, jalapeño, dry chilies, and additional salsa ingredients like tomatoes, green tomatoes, and onion.

Neighbors do not decrease their purchases of fresh goods, even though there are 15% fewer shops, implying a potential increase in sales of fresh products per shop. Losing sales of non-fresh products while maintaining sales of fresh ones may be an even worse scenario for shops if fresh products are less profitable. However, I find that there is no negative effect on shops' gross profit margin (see Figure 3). Hence, the expansion of chains is not pushing shops to unprofitable niches. It is the decline in revenue and not a decline in profitability that is driving the reduction in shops' profits. This null effect on the revenue of fresh products also has relevant implications for the external validity of the findings. In particular, what would happen if the number of chain stores continues growing and doubles or triples their current number? These findings suggest that shops will continue to lose revenue on non-fresh and standardized products. Still, they will retain revenue from fresh products, potentially leading to the specialization of shops in fresh products.

There are several potential reasons for shops retaining their sales of fresh products. Shops might have an advantage over chains in offering these products ripe and fresh because of differences in sourcing: shop owners go to the central market or a nearby bakery every day and select these products. Freshness and ripeness are even more relevant in a context where consumers are cash and credit constrained and buy products to consume the same day, which is consistent with lower-income households purchasing more often and a larger

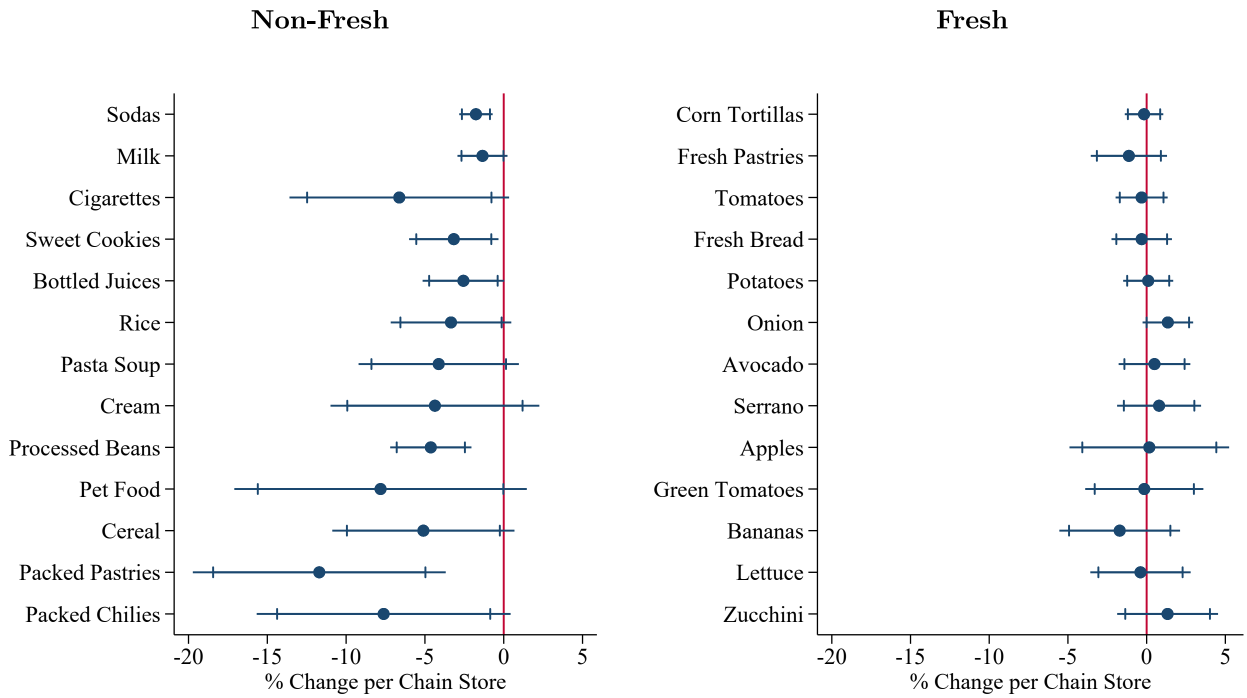


Figure 4: Effect on Neighbors Expenditure in Shops

Note: The figure displays the estimation and the 90 and 95% confidence intervals of the estimation of equation 3 using 2SLS, replacing the dependent variable with household-level expenditure in pesos for each of the goods. The percentage change is computed by dividing the estimated effect by the household average expense in shops of that product. The effects are for each additional chain store. Goods are sorted by their share of shops' revenue from top to bottom. For non-fresh goods, sodas represent 13% of revenue and packed chilies 0.2%. For fresh goods, corn tortillas represent 7% of revenue and zucchini 0.2%.

share of their food in shops (see Figure A.15). The following section discusses comparative advantages that allow shops to survive in more detail.

6 Discussion

This section discusses why shops survive despite their disadvantages in scale and estimates the consumer welfare effects of the expansion of chains. First, I estimate a discrete choice model to highlight the drivers behind the consumers' decision to purchase in a neighborhood shop or a convenience chain. These drivers include, among others, distance to the closest shop and chain, whether the household is purchasing fresh products or alcohol and tobacco, whether the payment method is using informal credit or electronic means, household income, and the age of the household head. Then, I show that the adverse effects of chains on shops are smaller for owner-operated and smaller shops. I present results consistent with these smaller and owner-operated shops having comparative advantages in building relationships with their customers, offering more variety and tailoring it for their consumers, facing lower agency costs, and screening their neighbors to provide them with informal credit to buy in the shop. The second subsection estimates the welfare effects of the expansion of chains and the decrease in the number of neighborhood shops through five distinct channels following Atkin, Faber and Gonzalez-Navarro (2018).

A. Shops' Comparative Advantages

I estimate a conditional discrete choice model to highlight the drivers behind the consumers' decision to purchase in a neighborhood shop or a convenience chain. The conditional choice model allows for a neat interpretation of the estimates by comparing purchases of households located in the same census tract in the same year. In particular, I use the following standard specification:

$$\Pr\left(\mathbf{y}_i \mid \sum_{t=1}^{T_i} y_{it} = k_i\right) = \frac{\exp\left(\sum_{t=1}^{T_i} y_{it}\mathbf{x}_{it}\boldsymbol{\beta}\right)}{\sum_{\mathbf{d}_i \in S_i} \exp\left(\sum_{t=1}^{T_i} d_{it}\mathbf{x}_{it}\boldsymbol{\beta}\right)} \tag{4}$$

Where i denotes the census tract by year group, t denotes the transaction, which is at the household-by-day-by-establishment level,[15] y_{it} takes a value of 1 if the transaction occurred in a neighborhood shop and 0 if it occurred in a convenience chain, $\mathbf{y}_i = (y_{i1}, \ldots, y_{iT_i})$ denotes the vector of purchase locations for group i, $\mathbf{x}_{it}$ is the vector of covariates, k_i is the number of transactions in a neighborhood shop in group i, and d_{it} is equal to 0 or 1 such that $\sum_{t=1}^{T_i} d_{it} = k_i$.

Comparing households living in the same census tract, I find that those with a neighborhood shop 500 meters closer to their home are 21 percentage points (pp) more likely to choose the shop over the convenience chain. Those who buy fresh products or pay using informal credit are 29pp and 14pp more likely to prefer the shop. These shop advantages have probably always existed and did not emerge as a response to chains because even in the early consumption data, 2006 and 2008, the share of consumption paid for using informal credit was 3 to 10 times higher in shops, and the share of consumption in fresh products was 3 to 5 times larger. Relationships between shops and neighbors are hard to measure, but they likely grow with time. Data on how long a customer has lived in a neighborhood are unavailable. However, suppose that homeowners have lived, on average, longer in the neighborhood or are more involved with the community. In that case, home ownership could be used as a proxy for the strength of the relationship with shops. Within the same neighborhood, households that own their house are 6pp more likely to purchase in the shop. Similarly, those with a household head in the fifth age quintile are 6pp more likely to prefer the shop than those in the first quintile.

On the other hand, those purchasing alcohol or tobacco, paying using a credit or debit card, or owning a car are 40, 37, and 4 pp more likely to purchase in a convenience chain. Relative to the lowest quintile of the income distribution, the wealthiest quintile is 13pp more likely to prefer the convenience chain.

Motivated by the drivers of purchasing in shops or chains, I explore whether the effects of chains on shops vary based on shops' size and management type. First, I compare the effect of chains on neighborhood shops and hybrid stores. Hybrid stores represent close to 3% of the establishments in this segment. They are different from shops because they are less differentiated from chains, which is why they share the classification code with chains in the Economics Censuses (different from the one of shops). In particular, hybrid shops hire employees, are similar in size to chain stores, have larger catchment areas, and are more likely to provide parking spots.[16] However, hybrid stores are different from chains because their owners only have one store. This is the only analysis that includes hybrid stores.

Figure A.9 compares the effects of chains on neighborhood shops and hybrid stores using the interaction of the number of chain stores with a dummy representing hybrid stores as a second endogenous variable and the interaction between the instrument and the same dummy as a second instrument. The data are

[15] All the goods purchased by the household in a store type in a day are considered as one transaction, because the ENIGH does not separate the visits within a day.

[16] Figure A.1 displays an example of a hybrid store.

Table 5: Buying in Shops vs. Chains

	1[Purchase in Neighborhood Shop]									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Closest Shop (km)	-0.508***	-0.474***	-0.462***	-0.454***	-0.451***	-0.452***	-0.436***	-0.441***	-0.432***	-0.420***
	(0.105)	(0.0984)	(0.0988)	(0.0976)	(0.0976)	(0.102)	(0.0949)	(0.0959)	(0.0997)	(0.100)
Fresh Product		0.382***	0.379***	0.348***	0.348***	0.341***	0.277***	0.287***	0.303***	0.290***
		(0.0133)	(0.0133)	(0.0133)	(0.0134)	(0.0141)	(0.0193)	(0.0197)	(0.0213)	(0.0216)
Credit			0.170***	0.158***	0.158***	0.178***	0.146***	0.143***	0.148***	0.144***
			(0.0509)	(0.0471)	(0.0471)	(0.0476)	(0.0385)	(0.0413)	(0.0435)	(0.0415)
Homeowner				0.063***	0.063***	0.059***	0.051***	0.059***	0.071***	0.055***
				(0.0130)	(0.0130)	(0.0134)	(0.0118)	(0.0120)	(0.0123)	(0.0129)
Electronic Payment					-0.407***	-0.376***	-0.394***	-0.384***	-0.366***	-0.367***
					(0.0259)	(0.0288)	(0.0350)	(0.0345)	(0.0342)	(0.0356)
Alcohol or Tobacco						-0.392***	-0.411***	-0.405***	-0.392***	-0.397***
						(0.0133)	(0.0145)	(0.0143)	(0.0148)	(0.0149)
Closest Chain (km)							0.267***	0.264***	0.273***	0.273***
							(0.0540)	(0.0565)	(0.0590)	(0.0570)
Own Car								-0.071***	-0.045***	-0.043***
								(0.0127)	(0.0123)	(0.0120)
Income Quintile=2									-0.022	-0.018
									(0.0164)	(0.0162)
Income Quintile=3									-0.031	-0.028
									(0.0201)	(0.0202)
Income Quintile=4									-0.067***	-0.064***
									(0.0178)	(0.0181)
Income Quintile=5									-0.126***	-0.124***
									(0.0194)	(0.0198)
Age Quintile=2										0.027*
										(0.0145)
Age Quintile=3										0.023
										(0.0159)
Age Quintile=4										0.033**
										(0.0166)
Age Quintile=5										0.060***
										(0.0203)
Observations	161,081	161,081	161,081	161,081	161,081	161,081	161,081	161,081	161,081	161,081

Note: The table displays the marginal estimates and standard errors clustered at the census tract level of a choice model conditional on year by census tract where the dependent variable takes a value of 1 if the transaction occurred in a neighborhood shop and 0 if it occurred in a convenience chain. Consumption data are from ENIGH 2008, 2014, and 2018 and distances to the closest shop and chain are based on the establishments in the Economic Censuses of 2009, 2014, and 2019. Distances are measured based on the centroid of the block where the household and establishments are located and are capped at 1km. Fresh products and alcohol or tobacco are dummies, indicating whether the household bought these products that day (the omitted category is other products). Credit and electronic payment are dummies for the household paying using informal credit or electronic payments (credit/debit card); the omitted category is cash and other payment methods. Homeowner and Own Car are indicators that take a value of one if the household does not pay rent and owns a car. The income quintiles are based on the household's income, and the age quintiles are based on the head of the household's age.

at the neighborhood-city-year-shop type level. Hybrid stores are significantly more affected by chains. At the neighborhood level, their drop in profits and value-added are 80% larger than for neighborhood shops. At the store level, the differences are starker. The percentage reductions in profits, value-added, and hired employees for hybrid stores are more than double those for shops.

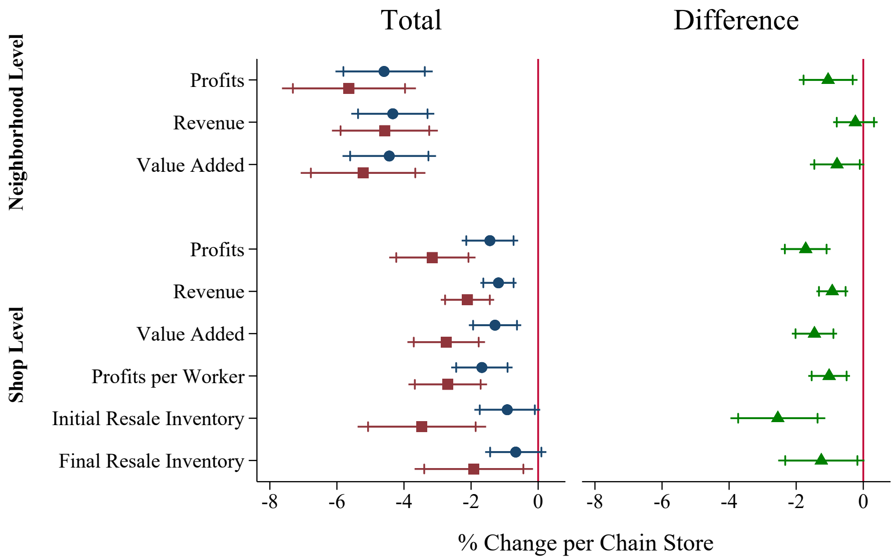


Figure 5: Effects of Chains on Shops' Performance by Type of Management

Note: The figure displays the estimation and 95% confidence intervals of equation 3 using 2SLS but adding i) the interaction of number of chain stores and a dummy variable for whether the average/sum is for an owner-operated shop to the second stage and ii) the interaction of the instrument and the same dummy to the first stage. The dependent variable in equation 3 is the inverse hyperbolic sine of the row label.

Almost all shops are owner-operated, potentially giving them a comparative advantage over chains. The customer experience is likely better if customers purchase directly from the owner, whom they know and who is often a friend and neighbor. These relationships could also allow shops to tailor their product mix to match customers' tastes and offer their neighbors store credit when they can not pay for products because of facing liquidity constraints. In Figure 5, I compare the effect of chains on shops that hire employees (7% of all shops) and on owner-operated ones. On aggregate (neighborhood level), the decline in revenue, value-added, and profits is 5-22% for shops that hire employees. At the shop level, those hiring employees suffer at least 60% larger declines than owner-operated shops in profits, value-added, revenue, profits per worker, and inventories.

Owner-operated shops may have a smaller negative effect because of lower agency costs. The owner is the residual claimant of profits, making her incentives, different from those of employees, naturally aligned with what is best for the business. Lower agency costs are more advantageous the higher the effort required to perform a task or the harder it is to monitor it. Consistent with shops having advantages from lower agency costs, Figure 4 shows that shops retain their sales of fresh products like fresh bread, fruit, and vegetables. These products require higher effort in sourcing because shop owners go to the central market daily to select them. Moreover, these products are not standardized, and offering them fresh, and ripe requires additional effort. For example, different from a can of Pepsi that has no variation in quality, effort makes the difference between offering a yellow (ripe) banana instead of a green (unripe) or brown (rotten) one.

Shops also have an advantage in offering a wider and tailored product mix. There are 247 food product categories in ENIGH 2018 (e.g., corn tortillas, tomatoes, Oaxaca cheese, and pork shoulder). At the city level, consumers purchase, on average, 12 food product categories in chain stores and 88 food categories in shops. However, this difference may be driven by consumers being more likely to buy in shops or shops having more variety. Conditional on purchasing in convenience chains, households purchase 12 food product categories in chains and 26 in neighborhood shops. These differences are consistent with shops offering more variety of products than chains. To test whether shops have a product mix customized to local preferences, I categorize product categories from the ENIGH by rareness. Rare product categories are those that households purchase only in less than 20% of the cities. At the city level, families buy 96% of these rare product categories exclusively in shops, 2% in chains, and 2% in both. Even if only considering households that purchase in chains, shops would still seem to have a more tailored product mix because families buy these rare products exclusively in shops 70% of the time, 20% in chains, and 10% in both.

Relationships are hard to measure, but using homeownership as a proxy for them in the discrete choice model suggests that they matter. Building on this mechanism, I use whether the shop pays rent or not as a proxy for whether the shop is next to the owner's house. Shops in the owners' houses will likely have stronger relationships because the owner is also a neighbor. Figure 6 shows that the adverse effects of chains are significantly larger for shops that pay rent. At the neighborhood level, the percentage reduction for shops that pay rent relative to those that do not is 14% larger in profits and 7% larger in revenue. At the shop level, the percentage reduction for shops that pay rent is profits, revenue, value-added, profits per worker, hired employees, and inventories is at least 60% larger.

An alternative to proxy for relationships is using the age of the shop. A limitation is that old shops might have grown old because they are resilient to adversity. Hence, chains affecting older shops less than younger ones is consistent with older shops having an advantage in relationships, being more resilient in general, or both. Nonetheless, I present results for heterogeneity of shops' age as well. I define old shops as those in the fifth quintile of the age distribution of shops and young shops as all the others. The average age of young shops is five years, and the average age of old shops is 19. Figure A.10 shows that the adverse effects of chains are significantly smaller for old shops. The percentage reductions in revenue, profits, value-added, profits per worker, and revenue per worker for young shops, are more than three times larger than for old shops. Older shops having more and stronger relationships is consistent with these results. However, these results are also consistent with older shops having more human capital specific to operating a shop and responding better to competition.

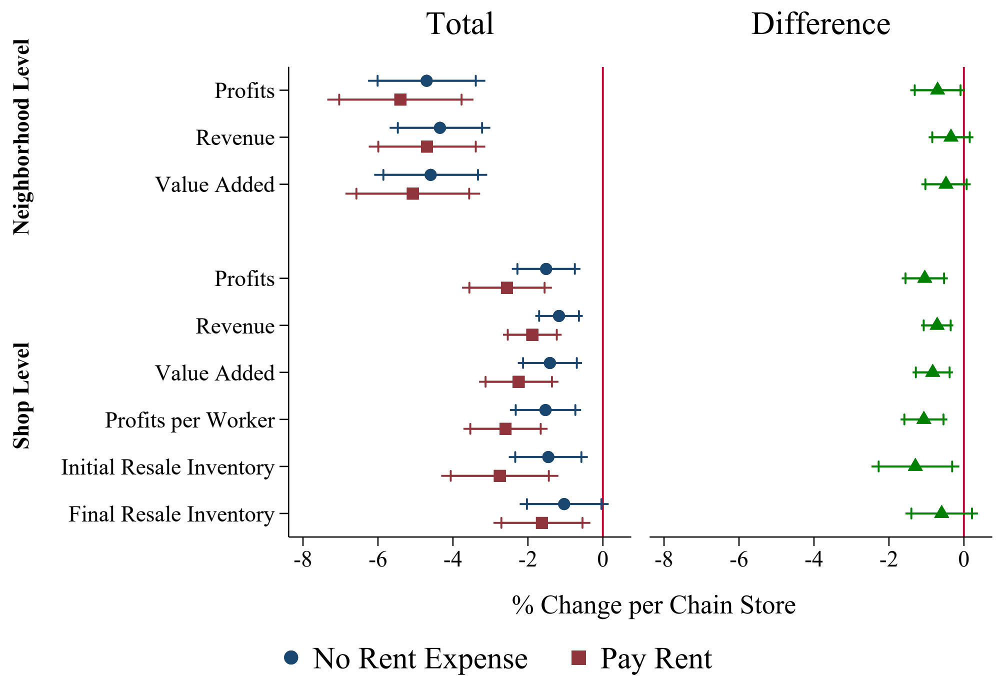


Figure 6: Effects of Chains on Shops' Performance by Whether they Pay Rent

Note: The figure displays the estimation of Equation 3 using 2SLS but adding i) the interaction of the number of chain stores and a dummy variable for whether the average/sum is for shops that pay rent and ii) the interaction of the instrument and the same dummy to the first stage. The dependent variable in equation 3 is the inverse hyperbolic sine of the row label. Ninety and 95 percent confidence intervals plotted.

Relationships between shop owners and neighbors may also allow shops to screen their neighbors better and offer them informal credit to purchase in the shop. Consistent with shops having a comparative advantage in providing credit to their neighbors, shops supply 16% of all the credit households use to buy food and beverages. Moreover, they provide 69% of the credit families use in the first income quintile to purchase food and drinks.[17]

The evidence in this section points to shops having comparative advantages in offering fresh products and informal credit, building relationships with their customers, closeness to their customers, and tailoring their product mix. These are attributes that consumers may miss due to the reduced number of neighborhood shops. However, the expansion of chains allows consumers to access amenities unavailable in shops. The following section considers these and other forces to estimate the welfare effects of the expansion of chains.

B. Consumer Welfare

The expansion of chains that, in turn, reduces the number of neighborhood shops can have positive and negative effects on welfare. On the one hand, chains reduce the profits of shop owners and decrease the availability of shops for consumers. On the other hand, chains create jobs and offer products and amenities that may not have been available in shops. I use the framework and code of Atkin, Faber and Gonzalez-Navarro (2018), to estimate the compensating variation of the expansion of chains, the change in household income required to make households indifferent between the nonexistence of chain stores and their flourishing.

[17] Author's calculations based on ENIGH 2018.

The methodology decomposes the welfare effects of the expansion of chains into three effects on the household cost of living and two effects on nominal household incomes.[18] The cost of living effects are the effect on shops' prices (procompetitive price effect), the effect from the reduction in the number of shops (procompetitive exit effect), and the direct price index effect that includes the gains from being able to purchase in convenience chains, such as differences in prices, variety, and store amenities. The effects on nominal household incomes are the effect on employment and wages in the retail segment and the retail profits of owners. This section discusses the quantification results, and the Online Appendix D includes more details on the estimation.

I estimate the cost of living effect under a CES demand system (main specification) and use a first-order approximation based on observed price differences. The main difference in interpretation is that the CES alternative captures the effects on welfare from changes in variety and amenities, while the first-order approximation ignores these because, basically, it assumes that chains have always existed and shops do not exit. I start discussing the estimates using the CES demand system and then go through the implications of the observed differences between the CES and the first-order methodologies.

Based on revealed preference (ex post market shares), higher-income households are those who value shops the least and chains the most (Figure A.15). In the quantification, these two forces, captured by the procompetitive exit and the direct price index, are the largest contributors to the overall welfare effect. Since convenience chains are not cheaper, the direct price index effect captures the gains from varieties and amenities of purchasing in chains, which include parking, air conditioning, flexible hours (24/7), and acceptance of electronic payment methods. The rich appreciate these amenities the most; hence, the gain from the direct price index for the rich is more than 20% larger, reaching 3.2%.

On the other hand, the procompetitive exit effect is the loss of welfare due to the reduced number of neighborhood shops. It is the largest for the poor (2.9%) and decreases throughout the income distribution, it being half the magnitude for the rich (1.5%). This is driven by poor households, who are more cash and credit-constrained, appreciating shops and their amenities the most, such as informal credit, relationships with the owner, closeness to home, broader and tailored product mix, and ripeness of products.

Consistent with the main driver of the welfare effect being the amenities no longer available at shops and those now available at chains, the first-order approximation displays much smaller welfare gains and losses (Figure A.16). The procompetitive effects are null, because there is no effect on shops' prices nor, by assumption, on their availability. The direct price index effect becomes negative because chains are a little more expensive than shops, and without considering amenities, replacing shops with chains is just a price increase. In summary, in the CES model, the direct price index and the pro-competitive exit effects are large because it considers the change in availability of the amenities and varieties offered at chains and shops. However, in the first-order approximation, they become null by implicitly assuming that chains and shops have always existed.

The income effects mostly cancel each other out because labor income from new jobs at convenience chains compensates for lost income from shop owners' profits. The expansion of chains leads to 10.69% fewer shops. Hence these households lose this source of income. Moreover, for the shops that do not close, profits decline by 5.8%. However, chains also create a new source of income for households by creating jobs. On average, the decrease in jobs in shops (including owners) and the increase in jobs in chains wash out (Table A.5). In the quantification, the increase in retail labor income from the job creation of chains compensates

[18] I do not include as a potential channel the indirect effect on other sources of household income from other sectors, such as manufacturing and agriculture.

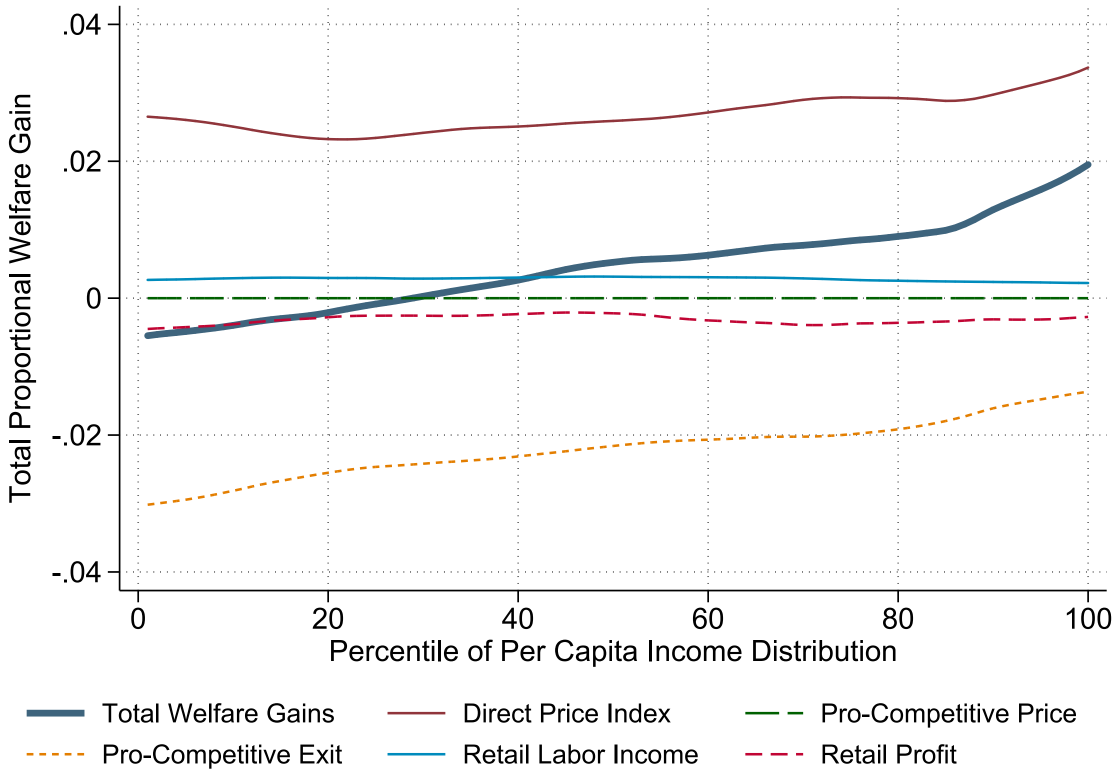


Figure 7: Welfare Effects

Note: The graph displays the non-parametric plots of the effect of the expansion of chains and the reduction in the number of shops on household welfare using a CES demand system to estimate the cost of living effect. The quantification exercise is described in the Online Appendix D and Section 6 . The plot corresponds to the average of 1,000 bootstraps described in the Online Appendix D.

for the loss in retail profits of shop owners. However, because shop owners' profits are higher than wages at convenience chains, the negative effect of the retail profit (0.31%) is 10% larger than the positive retail labor income effect (2.8%).[19]

In summary, the cost of living is the main driver of the welfare effects because the income channels have a smaller magnitude and mostly cancel each other out. The richest households are the ones who appreciate the least the existence of shops and value the most chains' entry, and vice versa for the poor, leading to a welfare gain of 1.6% for the richest and a welfare loss of 0.5% for the poorest.

7 Robustness

This section presents robustness checks for alternative specifications, alternative IVs, neighborhood sizes, controls, and standard errors.

The results have focused on the contemporary effect of convenience chains on neighborhood shops. However, there may be longer-term effects on shops. To examine this possibility, Table A.3 presents the results of three specifications in long differences (Columns 2 - 4). For these specifications, the outcome is the change in the number of neighborhood shops from 2004 to 2019, the instrumented variable is the change in the

[19] Based on the 2019 Economic Census, an average shop makes 9,500 MXN of monthly profits and 1.5 family members work there, hence 6,300 MXN per person. An average production, sales, and services employee in a convenience store makes 6,200 MXN minus taxes and social security.

number of convenience chain stores between 2004 and 2019, and the instrument uses 1999 chains stores in nearby cities to predict the change in the number of chain stores (the same that the main specification uses to predict the number of chain stores in 2004). The estimate in column 2 has no fixed effects and no controls (-3.82, SE = .368); column 3 adds controls for the change in the economic activity (-4.84, SE = .771); and column 4 adds city fixed effects (-4.88, SE = .490). These estimates suggest that the contemporaneous effect is between 79-100% of the long-term effect. This seems reasonable because contemporaneous means 5-year windows (time between census), and most of the effect is through a decrease in entry, which should adjust much faster than exits.

Other alternative specifications are transforming the number of stores variable to the natural logarithm of the number of stores. Column 4 uses the natural logarithm of the number of shops as the dependent variable, and Column 5 uses the natural logarithm of the number of shops as the dependent variable and the natural logarithm of the number of chain stores as the dependent variable. The results are consistent with those of the main specification. For example, an increase from zero to the average number of chain stores in the neighborhood reduces the number of shops by 19% in the log-linear specification.

Table A.7 presents the results for alternative IV specifications. All these specifications provide estimates similar and consistent to those of the main specification. The main specification is in column 1. Column 2 presents results using one IV per chain (instead of aggregating across chains), and Column 3 uses a polynomial of the instrument that includes its square and cube. These two specifications provide similar results with smaller standard errors but have two disadvantages. The first is that the first stage of the IV is weaker, and second, testing the monotonicity assumption, placebo tests, and heterogeneity analysis are more transparent with just one instrument. To construct the economies of scale component of the IV, I aggregate the number of chain stores in second-degree neighboring cities (adjacent and those adjacent to adjacent cities)—columns 4 and 5 present results for using first and third-degree neighboring cities instead with consistent estimates.

To construct the economies of scale component of the IV, I aggregate the square of the number of stores in second-degree neighboring cities across chains and take the square root of the sum (Herfindahl-Hirschman without normalization). Columns 6 and 7 present alternatives leading to a similar estimate but with a weaker first stage. Column 6 does not square root the sum, and column 7 does not square the number of stores at the chain level and subsequently does not take the square root.

To construct the suitability for the chains component of the IV, I use the prevalence of wide streets in the neighborhood—columns 8 to 10 present results using alternative measures of suitability. In columns 8 and 9, I create a measure of suitability in two stages. The first stage is a lasso regression of the number of chain stores in each census tract obtained from the 2020 firm directory (DENUE) on explanatory variables. The second stage is to predict the number of chain stores using the lasso-selected variables and estimates. This prediction is the measure of suitability used. The variables include sociodemographic characteristics at the census tract and municipality level from the 2000 and 2010 population census, street data from open street maps, and municipality-fixed effects. Columns 8 and 9 differ because column 9 does not include the 2000 population census variables. The lasso estimations also include each variable's square, cube, and natural logarithm transformation totaling more than 2,600 variables in each analysis. The lasso in column 9 selected 675 variables, and the one in column 10 selected 373 variables. The prevalence of wide streets in the census tract was one of the three variables with the largest magnitude coefficient in both lasso estimations. In Column 10, I use the number of chain stores and hybrid stores in each neighborhood in 1999 (before more than 90% of the openings of chains) as a suitability measure. The idea behind this specification is that neighborhoods suitable for hybrid stores in 1999 were also suitable for chains in the following two decades. Finally, column 11 uses the contemporaneous number of chain stores in nearby cities instead of the lagged ones to construct the instrument.

Table A.8 presents results adding different sets of controls to the main specification. Column 2 controls for the number of convenience chain stores in nearby neighborhoods constructed as the number of chain stores in the 2km radius neighborhoods that are not in the 1km radius neighborhoods. Column 3 uses the principal components with an eigenvalue larger than one instead of the factors from the factor analysis to control for the presence of other businesses in the neighborhood. Column 4 controls for the number of supermarkets in the neighborhood. Column 5 is the main specification without the economic activity controls from the factor analysis. Column 6 adds controls from the 2000 and 2010 population census, including the average age of household head, household income, hours worked, population, and the number of households, interpolated and extrapolated linearly. Column 7 restricts the sample to neighborhoods for which there are ENIGH data. Column 8 includes the following household controls from ENIGH: number of inhabitants, men, women, adults, and minors; expenses on clothing, shoes, home, rent, energy, healthcare, public transportation, education, income, total expenses, and income per capita. Column 9 uses factor analyses to control for the same household characteristics keeping the factors with an eigenvalue larger than one.

Table A.9 shows the breakdown of the effect of the rise of chains on the number of shops by city size. The magnitude of the effect is larger for bigger cities. For towns with an average population of 14,000, the reduction in the number of shops is 11.3%; it is 13.5% for those with an average population of 262,000, and 20.8% for those with an average population of 880,000 thousand. Throughout the paper, the neighborhood definition was all the census tracts that would fall within 1 km from the center of each census tract. Figure A.11 contains the estimates of equation 3, but with alternative distances to construct neighborhoods: 0km (census tract level), 0.25km, 0.5km, 0.75km, 1km, 1.25km, 1.5km, and 2km. The magnitude of the effect is very similar across the specifications.

I cluster standard errors at the city level throughout the paper. Table A.10 contains standard errors of alternative clustering procedures. Column 2 clusters at the neighborhood and year level. Column 3 clusters at the city and year level. Column 4 clusters at the city-year level. Column 5 clusters at the city-year and neighborhood level. Clustering at the city level results in the largest standard errors, making the main specification the most conservative across clustering specifications.

Another concern in estimating standard errors is the potential correlation of unobserved shocks across adjacent cities or neighborhoods. Because of computational limitations, I cannot estimate standard errors that take into account these potential correlations in my full sample. Hence, I ran 250 iterations with 5,000 randomly selected neighborhoods. I compute the standard errors at the city level and take into account the potential correlation in errors across adjacent neighborhoods defined as those up to 0.5km, 1km, and 2km. The results, displayed at the top of Figure A.17, show that clustering at the city level is more conservative in every iteration.[20] The standard errors clustering at the city level are likely larger because they also account for potential positive correlation in errors across neighborhoods that are not adjacent but in the same city. I also estimate standard errors taking into account the potential correlation of unobserved shocks across adjacent cities and 2^{nd}-degree adjacent cities. The graph at the bottom of Figure A.17 shows that clustering at the city level, as done throughout the paper, is the most conservative alternative. In 80 percent of the

[20] I use the technique proposed by Colella et al. (2019) to account for potential spatial correlation of unobserved shocks and its companion statistical package *acreg*.

iterations, the standard errors clustering at the city level are not the largest.

In the discussion section, I show heterogeneity of the effect of chains on shops by whether the shop pays rent, hires employees, its age, and whether it is a shop or a hybrid. Figure A.14 repeats these analyses but controls for the distance between the shops and the closest chain. The estimates are very similar in magnitude, direction, and significance.

8 Conclusion

Developing countries have hundreds of millions of microenterprises. As these countries develop, their microenterprises face increased competition from larger, more efficient firms. Standard economic models predict that this process will reallocate resources from low-efficiency firms that downsize and exit to more efficient ones. However, microenterprises in developing countries continue to be overwhelming in number despite facing direct competition from larger firms offering similar and often identical products and services.

This paper contributes to understanding this phenomenon by studying how one of the most prevalent microenterprises, the neighborhood shop, responds to increased competition from the large expansion of convenience chains in Mexico between 1999 and 2019. I assemble a rich micro-data collection and pair two-way fixed effects with a novel instrument to address the endogeneity of chains' growth. I find that chains reduce the number of shops, primarily through a decrease in shop entry. However, most of them survive, and their customers continue to purchase in shops, but they buy less and less often, notably less packaged and standardized goods. I present evidence consistent with shops having comparative advantages stemming from being small and owner-operated, such as lower agency costs, building customer relationships, tailoring their product mix, and offering informal credit. Regarding welfare, the gains of chains substituting shops are increasing with household income.

The insights can be generalized to other industries and countries. The theoretical literature highlights how the relevance of comparative advantages defines industrial organization (Hubbard, 2004). For example, consumers' taste for fresh and ripe products determines the significance of the small businesses' comparative advantage in offering these products and, therefore, their survival. Hence, we can expect fragmented industries as long as the comparative advantages of being small and owner-operated are more extensive than those from economies of scale.

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Online Appendix A: Additional Tables and Figures

I Tables

Table A.1: Relationship Between the Instrument and Number of Retail Establishments

	Dependent Variable: # of Establishments									
Retail Establishments	Neighbor-hood Shops	Conv. Chains	Super-markets	Depart-ment Stores	Butcher	Poultry	Fish and Seafood	Fruits and Veg.	Non-alcoholic Drinks	Clothing Stores
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Economies of Scale$_{c,t-1}$ x	-5.09***	1.32***	-0.01	-0.05*	-0.09	0.00	-0.06	0.33	0.16	-0.18
Chain Suitability$_{m,c}$	(0.796)	(0.169)	(0.026)	(0.028)	(0.121)	(0.087)	(0.047)	(0.682)	(0.119)	(0.921)
Observations	158,515	158,515	158,515	158,515	158,515	158,515	158,515	158,515	158,515	158,515
Clustered SE	City	City	City	City	City	City	City	City	City	City

Note: The table displays the relationship between the instrument and the number of neighborhood shops. The first column includes the entire sample of neighborhoods, and the second column includes neighborhoods where chains have not yet entered.

Table A.2: Effect of Chains on Shop Survival

Dependent Variable:	Cox		Poisson				OLS			
Store Level (Exit=1)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Number of Chain Stores	0.044***	0.045***	0.044***	0.045***	0.030***	0.023***	0.019***	0.020***	0.013***	0.011***
	(0.0012)	(0.0012)	(0.0035)	(0.0036)	(0.0021)	(0.0045)	(0.0011)	(0.0012)	(0.0008)	(0.0018)
Observations	1,526,922	1,379,334	1,526,922	1,379,334	1,379,137	1,374,123	1,526,922	1,379,334	1,379,329	1,377,267
Store Controls		Y		Y	Y	Y		Y	Y	Y
Year x City FE					Y	Y			Y	Y
Neighborhood FE						Y				Y
Mean Dep. Variable | Chains>0	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40
Mean Chain Stores | Chains>0	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5

Note: The table displays the estimation of survival models. Columns 1 and 2 are Cox survival models. Columns 3-6 are survival models estimated using a Poisson and age of establishment fixed effect measured by the number of censuses the establishment has been open. Hazard ratios of Cox models and Poisson models after splitting on all observed failure times are identical (Royston and Lambert, 2011, Section 4.5). Hence, the coefficients of columns 1-2 and 3-4 are identical, but the standard errors reflect the differences in the underlining assumptions of each method. Columns 7-9 are OLS estimates with the age of establishment fixed effects.

Table A.3: Robustness: Alternative Specifications

Dependent Variable: # of Neighborhood Shops	2SLS	2SLS Long Differences	2SLS Long Differences	2SLS Long Differences	2SLS Log-Linear	2SLS Log-Log
	(1)	(2)	(3)	(4)	(5)	(6)
Number of Chain Stores	-3.85***	-3.82***	-4.84***	-4.88***	-0.03***	-1.81*
	(0.758)	(0.368)	(0.771)	(0.490)	(0.004)	(0.997)
Observations	158,515	34,182	33,987	34,182	158,515	158,515
Economic Activity Controls	Y				Y	Y
Year x City FE	Y				Y	Y
Neighborhood FE	Y				Y	Y
Δ Economic Activity Cont.			Y			
City FE				Y		
Mean Dep. Var. | Chains>0	175	-1.12	-1.12	-1.12	175	175
Mean Ch. Stores | Chains>0	6.7	7.3	7.3	7.3	6.7	6.7
From 0 to Avg. # Ch. Stores	-14.7%				-19.4%	
KP F-statistic	61.18	160.55	30.75	373.73	61.18	4.47

Note: The table displays the estimation of Equation 3. Columns 2-4 are long differences (2019-2004) of the number of neighborhood shops and convenience chains, and the instrument uses the economies of scale measure of 1999. Column 5 uses the natural logarithm of the number of shops as the dependent variable. Column 6 uses the natural logarithm of the number of shops as the dependent variable and the natural logarithm of the number of chain stores as the dependent variable.

Table A.4: Prices at Chains and Shops

	Dependent Variable: Log Price				
	ENIGH (Consumption Data)		Price Microdata		
	Food	Non-Food	All	Food	Non-Food
	(1)	(2)	(3)	(4)	(5)
I[Chain Store]	0.039***	0.010	0.109***	0.152***	-0.136*
	(0.003)	(0.011)	(0.041)	(0.046)	(0.079)
Observations	2,102,770	764,822	1,526	1,307	219
Household Charac. Controls	Y	Y			
Census Tract x Year x Product FE		Y			
Census Tract x Year x Product x Product Size FE	Y				
City x Year x Barcode FE			Y	Y	Y

Note: The table displays the difference in log price between convenience chains and neighborhood shops. Columns 1 and 2 use consumption data, and columns 3-5 use price microdata. The consumption data include quantities/sizes for food but not for other products.

Table A.5: Effect on Employment and Wages

	Employment		Log Wages	
		Excluding		Shops +
	All	Owners	Shops	Chains
	(1)	(2)	(3)	(4)
Number of Chain Stores	1.736	7.43***	-0.002	0.010***
	(1.494)	(0.401)	(0.003)	(0.003)
Observations	149,302	149,302	144,682	149,302
Economic Activity Controls	Y	Y	Y	Y
Year x City FE	Y	Y	Y	Y
Neighborhood FE	Y	Y	Y	Y
Avg. Dep. Var.|Chains>0	376.8	84.7		
KP F-Statistic	60.69	60.69	59.94	60.69

Note: The table displays the estimation of equation 3 using 2SLS, where the dependent variable is the number of jobs or the log wage. Column 1 is the effect on the total employed in chains and neighborhood shops, column 2 excludes the overhead jobs of chains, and column 3 excludes shop owners. Column 4 is the average effect on wages at shops, and column 5 is the average effect on wages at shops and chains.

Table A.6: Effect of Chains on Shops' Prices

	Dependent Variable: Log Price							
	Price Microdata			ENIGH (Consumption Data)				
	All	Food	Food	All	Food		Fresh	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Number of Chain Stores	0.000	0.000	0.000	0.002	0.002	0.002**	-0.008	-0.003
	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.001)	(0.009)	(0.005)
	[0.262]	[0.681]	[0.495]	[0.179]	[0.182]	[0.028]	[0.345]	[0.523]
Observations	110,516	81,944	28,572	11,970,529	9,822,768	8,479,123	981,984	722,721
Economic Activity Controls	Y	Y	Y	Y	Y	Y	Y	Y
Year x City x Barcode FE	Y	Y	Y					
Neigh. x Barcode FE	Y	Y	Y					
Year x City x Product FE				Y	Y		Y	
Neighborhood x Product FE				Y	Y		Y	
Year x City x Product x Size FE						Y		Y
Neigh. x Product x Size FE						Y		Y
KP F-statistic	64	60	62	55	58	47	44	36

Note: The table displays the estimation of Equation 3 using 2SLS, where the dependent variable is the log price. Columns 1 and 2 use price microdata, and columns 3-7 use consumption data. The consumption data includes quantities/sizes for food but not for other products.

Table A.7: Robustness: Alternative IV Specifications

Dependent Variable: # of Neighborhood Shops	Main	Per Chain	Squared & Cubed	1st Degree Neigh	3rd Degree Neigh	Squared Sum	Sum	Lasso1	Lasso2	Conv 1999	Non-Lag IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Number of Chain Stores	-3.85***	-3.64***	-3.76***	-3.25***	-4.38***	-3.26***	-3.67***	-2.36***	-2.28***	-3.50***	-3.67***
	(0.758)	(0.564)	(0.752)	(0.730)	(0.775)	(0.880)	(0.763)	(0.519)	(0.533)	(0.850)	(0.731)
Observations	158,515	158,515	158,515	158,515	158,515	158,515	158,515	158,515	158,515	158,515	158,515
Economic Activity Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Neighborhood FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year x City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Mean Dep. Variable | Chains>0	175	175	175	175	175	175	175	175	175	175	175
Mean Chain Stores | Chains>0	6.7	6.7	6.7	6.7	6.7	6.7	6.7	6.7	6.7	6.7	6.7
From 0 to Avg. # Conv. Stores	-14.7%	-13.9%	-14.4%	-12.4%	-16.8%	-12.5%	-14.1%	-9.0%	-8.7%	-13.4%	-14.0%
KP F-statistic	61.18	16.97	32.31	60.09	74.61	39.87	51.53	218.18	201.30	84.23	53.89

Note: The table displays the estimation of Equation 3 using 2SLS with variations of the instrument. Column 2 presents results using one IV per chain (instead of aggregating across chains), and Column 3 uses a polynomial of the instrument that includes its square and cube. Columns 4 and 5 present results using first and third-degree neighboring cities instead of second-degree ones. Column 6 does not take the square root of the square sum of chain stores in nearby cities. Column 7 does not square the number of chain stores in nearby cities before adding them up and does not take the square root of the sum. In columns 8 and 9, I create a measure of suitability in two stages. The first stage is a lasso regression of the number of chain stores in each census tract obtained from the 2020 firm directory (DENUE) on explanatory variables. The second stage is to predict the number of chain stores using the lasso-selected variables and estimates. This prediction is the measure of suitability used. The variables include sociodemographic characteristics at the census tract and municipality level from the 2000 and 2010 population census, street data from open street maps, and municipality-fixed effects. The difference between Columns 8 and 9 is that column 9 does not include the 2000 population census variables. The lasso estimations also include each variable's square, cube, and natural logarithm transformation totaling more than 2,600 variables in each analysis. The lasso in column 9 selected 675 variables, and the one in column 10 selected 373 variables. The prevalence of wide streets in the census tract was one of the three variables with the largest magnitude coefficient in both lasso estimations. In Column 10, I use the number of chain stores and hybrid stores in each neighborhood in 1999 to measure suitability. Column 11 uses the contemporaneous number of chain stores in nearby cities instead of the lagged ones to construct the instrument.

Table A.8: Robustness: Adding Controls

Dependent Variable: # of Neighborhood Shops	Main	Nearby Chains Control	Businesses PCA	Super-markets Control	Main No Controls	Pop. Census Controls	HH Sample	HH Controls	HH Controls FA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Number of Chain Stores	-3.847***	-3.774***	-4.476***	-3.848***	-4.825***	-2.832***	-4.047***	-4.237***	-4.112***
	(0.758)	(0.953)	(0.829)	(0.755)	(0.669)	(0.758)	(0.988)	(0.989)	(0.987)
Observations	158,515	158,515	158,515	158,515	158,515	152,138	49,354	49,354	49,354
Economic Activity Controls	Y	Y	Y	Y		Y	Y	Y	Y
Neighborhood FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year x City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Mean Dep. Var. | Chains>0	175	175	175	175	175	179	212	212	212
Mean Ch. Stores | Chains>0	6.7	6.7	6.7	6.7	6.7	6.8	9.4	9.4	9.4
From 0 to Avg. # Ch. Stores	-14.7%	-14.4%	-17.1%	-14.7%	-18.5%	-10.8%	-18.0%	-18.8%	-18.3%
KP F-statistic	61.18	49.07	79.62	61.08	103.81	54.06	81.59	78.39	81.30

Note: The table displays the estimation of Equation 3 using 2SLS with alternative controls. Column 2 controls for the number of convenience chain stores in census tracts more than 1 km away from but at most 2 km away. Column 3 uses the principal components with an eigenvalue larger than one instead of the factors from the factor analysis to control for the presence of other businesses in the neighborhood. Column 4 controls for the number of supermarkets in the neighborhood. Column 5 is the main specification without the economic activity controls from the factor analysis. Column 6 adds controls from the 2000 and 2010 population census, including the average age of household head, household income, hours worked, population, and the number of households, interpolated and extrapolated linearly. Column 7 restricts the sample to neighborhoods for which there is ENIGH data. Column 8 includes the following household controls from ENIGH: number of inhabitants, men, women, adults, and minors; expenses on clothing, shoes, home, rent, energy, healthcare, public transportation, education, income, total expenses, and income per capita. Column 9 uses factor analyses to control for the same household variables keeping the factors with an eigenvalue larger than one.

Table A.9: Effect by City Size

Dependent Variable: # of Neighborhood Shops	IV All Urban	Towns Avg. pop 14K	Cities Avg. pop 262K	Large Cities Avg. pop 880K
	(1)	(2)	(3)	(4)
Number of Chain Stores	-3.85***	-4.32***	-3.37***	-4.84**
	(0.758)	(1.503)	(0.746)	(1.835)
Observations	158,515	74,879	54,968	30,183
# of Cities	1,961	1,813	120	29
Economic Activity Controls	Y	Y	Y	Y
Neighborhood & Year x City FE	Y	Y	Y	Y
Mean Dep. Variable | Chains>0	175	125	192	201
Mean Chain Stores | Chains>0	6.7	3.3	7.7	8.6
Effect from 0 to Avg. # Conv. Stores	-14.7%	-11.3%	-13.5%	-20.8%
KP F-statistic	61.18	42.30	40.75	29.05

Note: The table displays the estimation of equation 3 using 2SLS splitting the sample by town size.

Table A.10: Robustness: Alternative Standard Errors

	Dependent Variable: # of Neighborhood Shops				
	(1)	(2)	(3)	(4)	(5)
Number of Chain Stores	-3.85***	-3.85***	-3.85**	-3.85***	-3.85***
	(0.758)	(0.444)	(0.752)	(0.627)	(0.546)
Observations	158,515	158,515	158,515	158,515	158,515
Economic Activity Controls	Y	Y	Y	Y	Y
Neighborhood FE	Y	Y	Y	Y	Y
Year x City FE	Y	Y	Y	Y	Y
Clustered SE	City	Neighborhood Year	City Year	City x Year	City x Year Neighborhood
KP F-statistic	61.18	37.95	28.07	80.56	106.59

Note: The table displays the estimation of Equation 3 using 2SLS clustering the standard errors at different levels.

II Figures

Figure A.1: Shops, Hybrid Stores, and Chains

Source: Google Maps.
Note: The figure contains an example of a shop (top left), a hybrid store (top right), and a chain store (bottom) in Saltillo, Mexico. Hybrid stores share the same establishment type code as Chains in the Economic Census, but different from Chains, the owners only have one store.

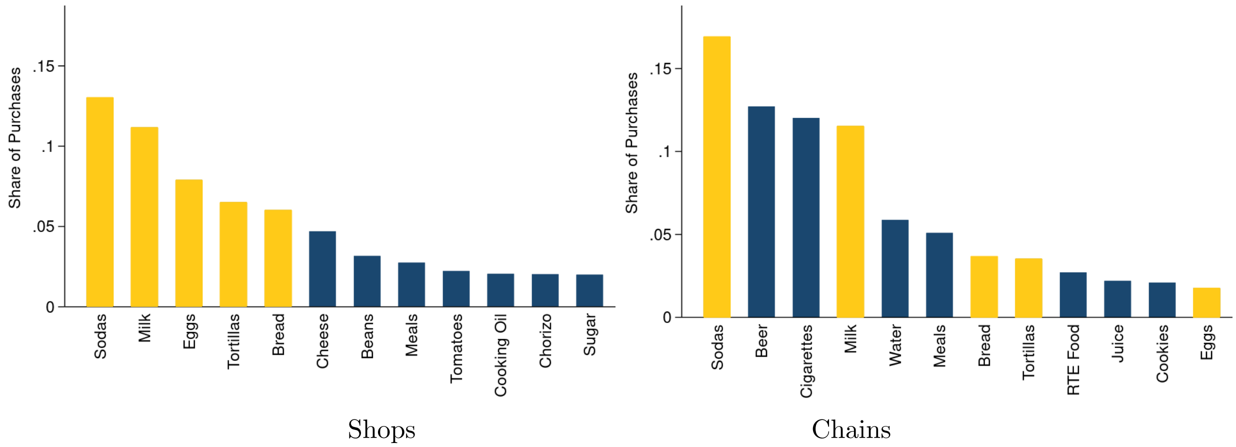


Figure A.2: Share of Store Sales for Top 12 Products
Source: Income and Expenditure Survey (ENIGH 2018)

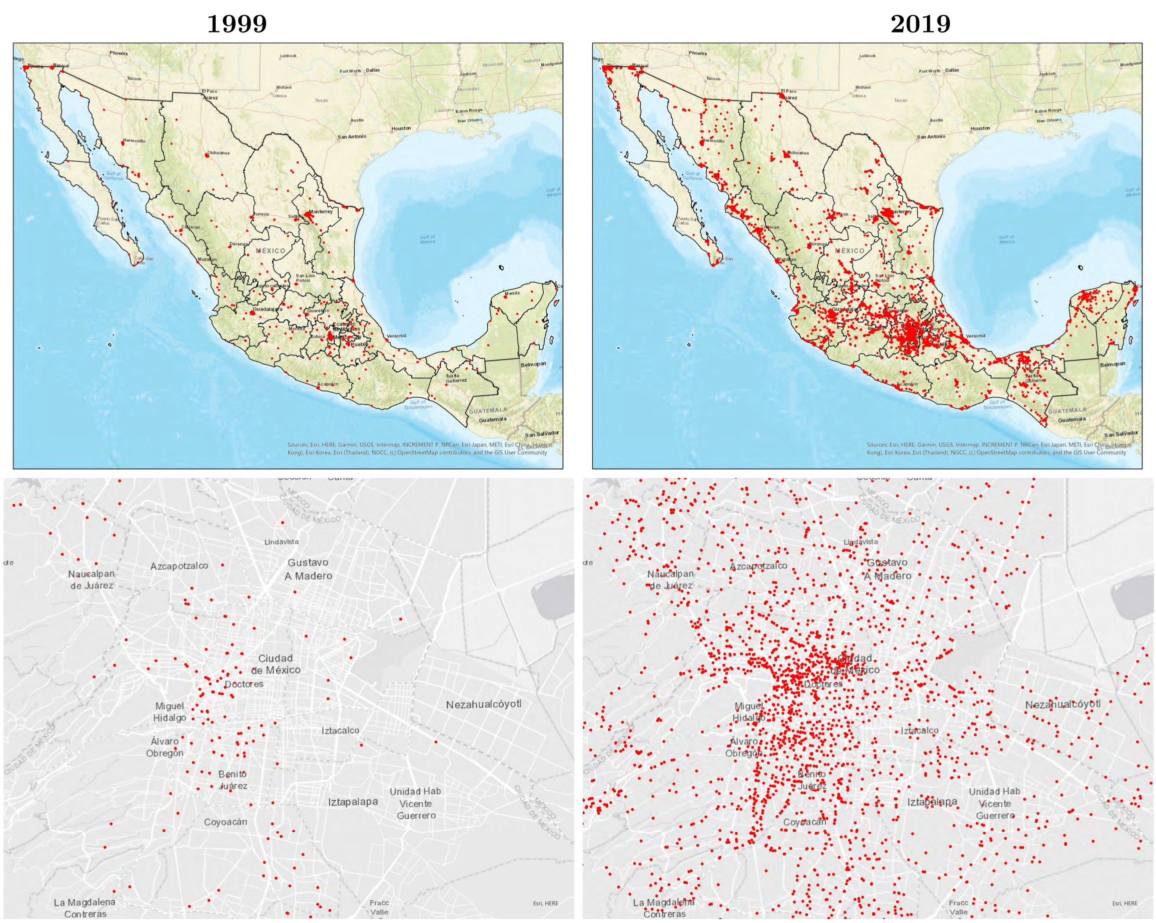


Figure A.3: Chain Stores Expansion
Note: The maps display the location of chain stores. A chain store is a store that belongs to a chain with more than 100 stores. Locations for 1999 are approximate using the 1999 Economic Census Data. Locations for 2019 are obtained from DENUE 2020.

A) Neighborhoods by Number of Chain Stores B) Neighborhoods by Number of Shops

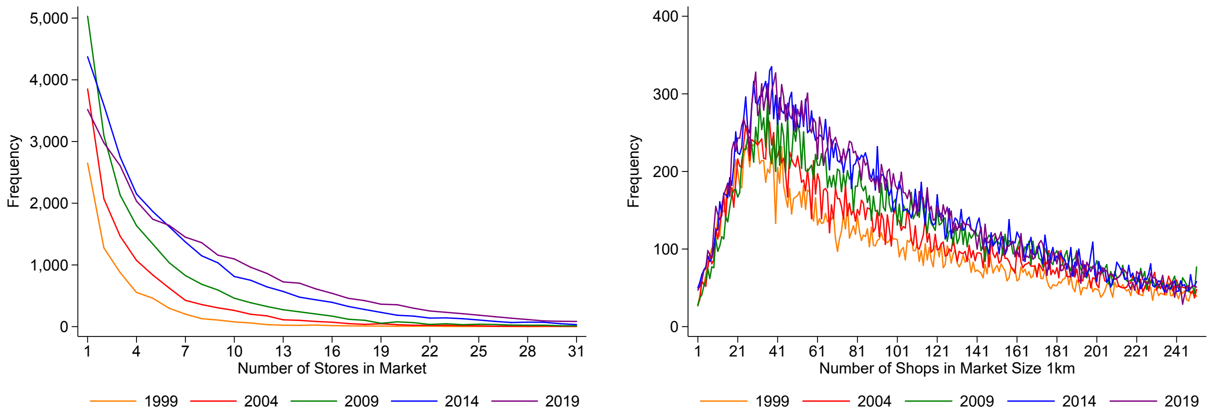


Figure A.4: Frequency Distribution by Number of Shops and Chain Stores

Note: The distributions of AGEBs by number of stores are computed using data from the 1999, 2004, 2009, and 2014 Economic Censuses. The AGEBs distribution by number of chain stores is conditional on the AGEB having at least one chain store.

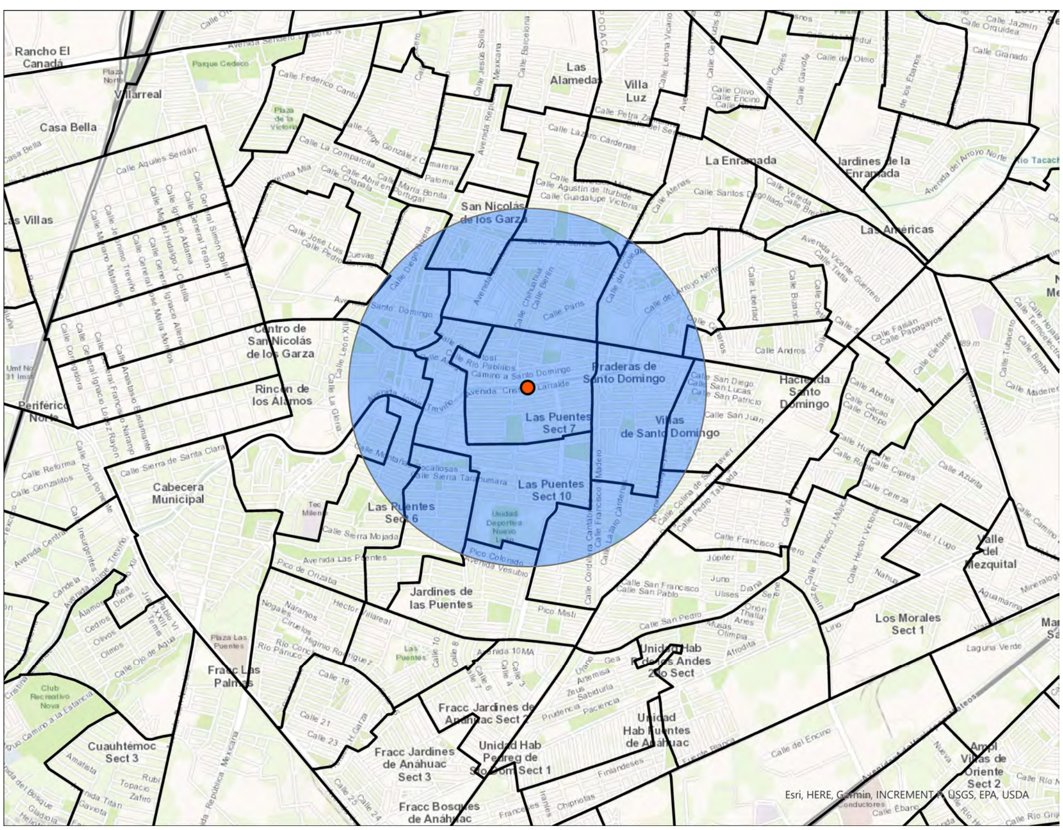


Figure A.5: Market Definition

Note: The map displays a 1km-radius circle with centered at the center of the AGEB. All the AGEBs that intersect with the circle define a neighborhood. The AGEBs shape and location is obtained from INEGI Marco Geostadístico.

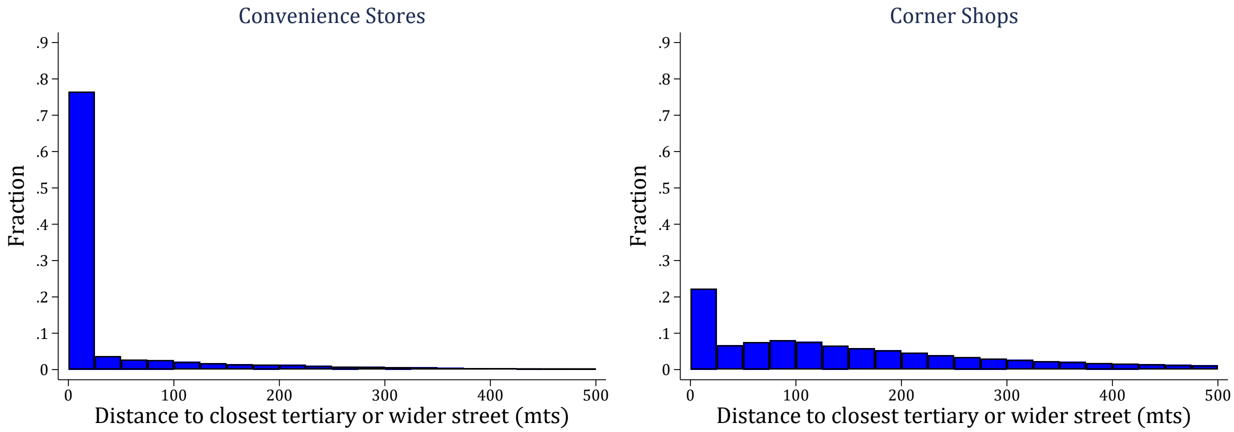


Figure A.6: Distance to Closest Wide Street

Note: The graphs display the distribution of distance from the store to the closest wide street. A wide street is defined as a street that is classified as trunk, primary, secondary, or tertiary by Open Street Maps. Streets location and type is obtained from Open Street Maps and stores locations are obtained from DENUE 2020.

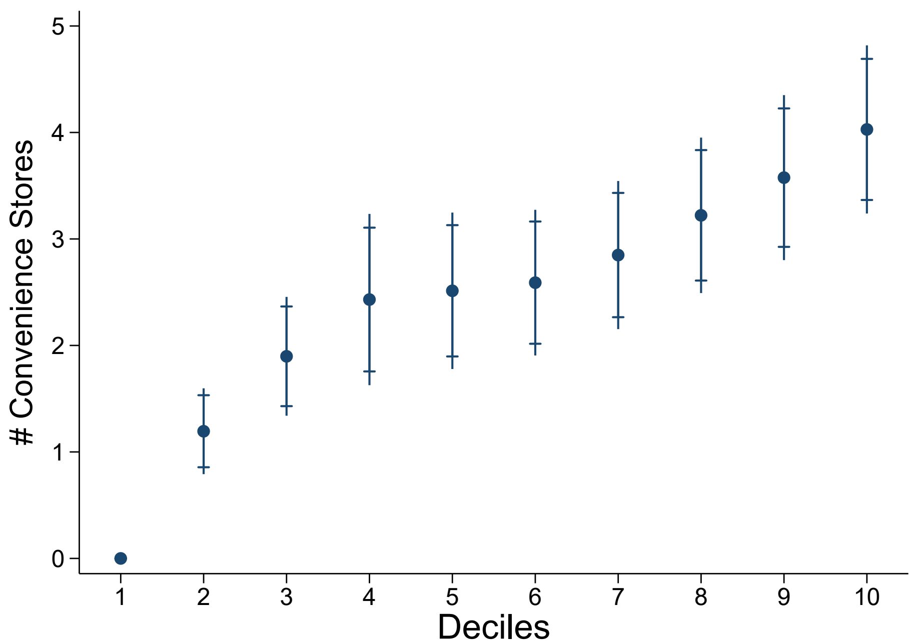


Figure A.7: Relationship between the Instrument and the Number of Chain Stores

Note: The figure displays the relationship between the instrument and the number of chain stores in the neighborhood. The figure displays estimates and 90 and 95% confidence intervals from a regression where the dependent variable is the number of chain stores in a neighborhood and the independent variables are dichotomous variables that take the value of 1 for each of the deciles 2 through 10 of the instrument. The estimation includes year-city and neighborhood fixed effects and controls for economic activity.

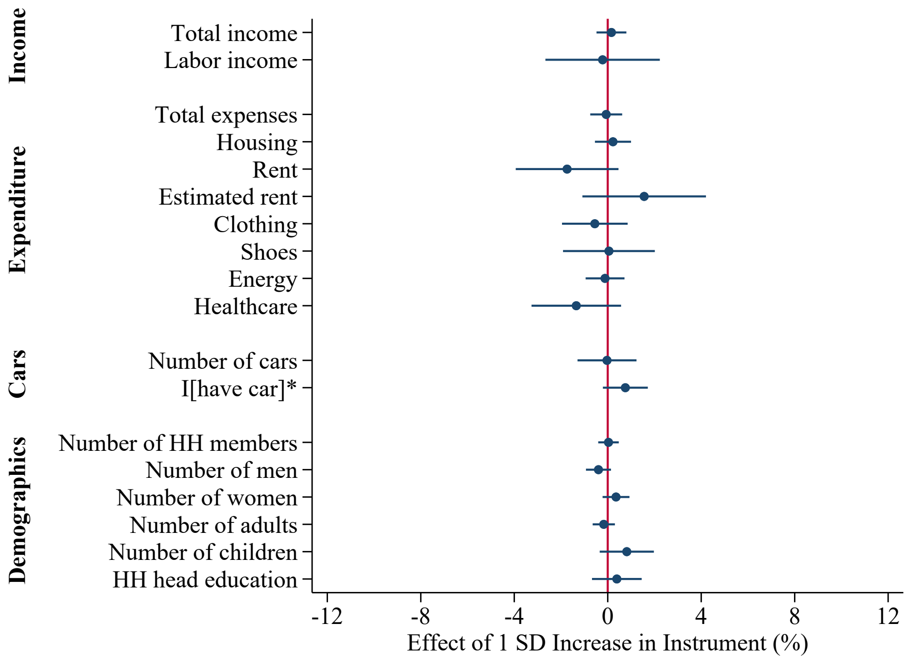


Figure A.8: Placebo: Relationship Between the Instrument and Household Characteristics

Note: The figure displays the estimates of regressing household characteristics on the instrument. Household characteristics vary at the household level, and the instrument varies at the neighborhood-year level.

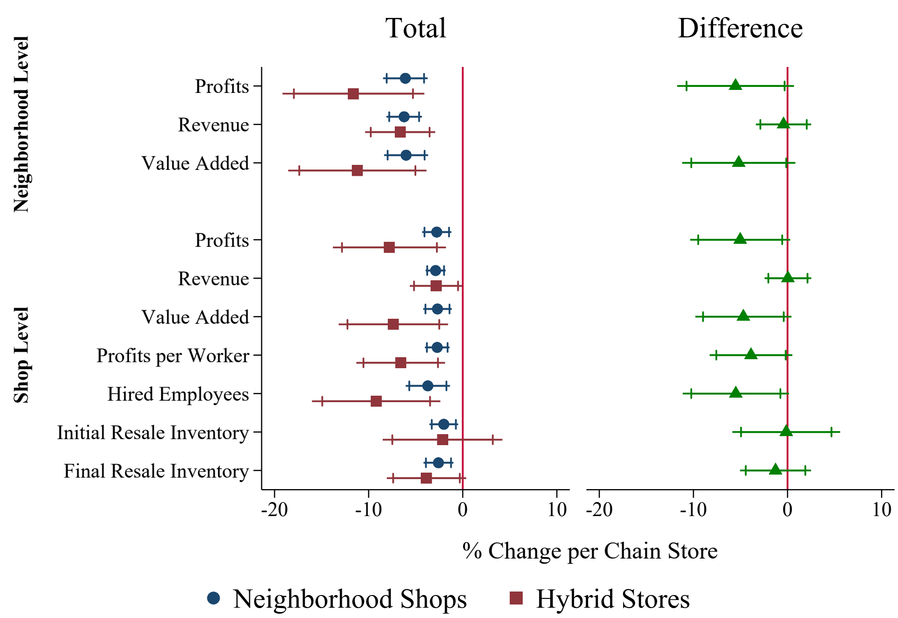


Figure A.9: Effects of Chains on Shops' Performance by Shop Size

Note: The figure displays the estimation and the 90 and 95% confidence intervals of equation 3 using 2SLS but adding i) the interaction of the number of chain stores and a dummy variable for whether the average/sum is for a hybrid store to the second stage and ii) the interaction of the instrument and the same dummy to the first stage. The dependent variable in equation 3 is the inverse hyperbolic sine of the row label.

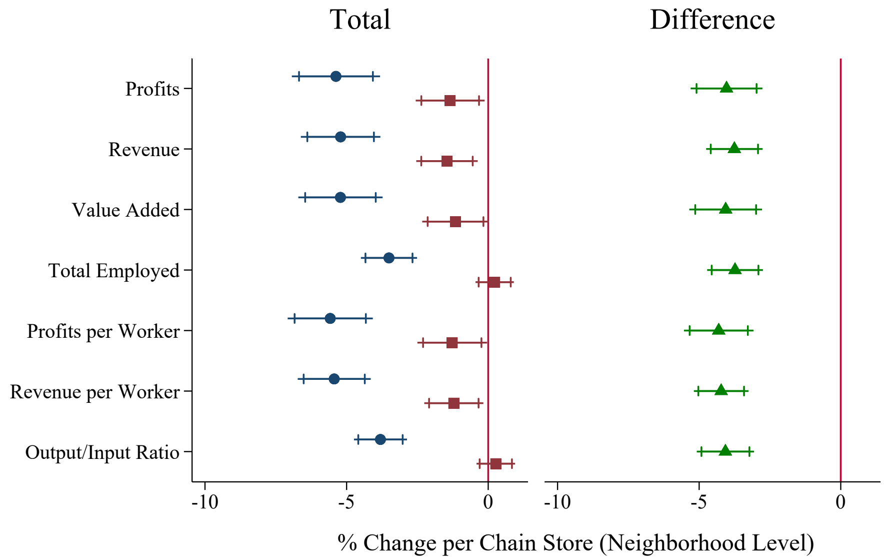


Figure A.10: Effects of Chains on Shops' Performance by Shop Age

Note: The figure displays the estimation of equation 3 using 2SLS but adding i) the interaction of the number of chain stores and a dummy variable for whether the sum is for shops in the fifth age quintile and ii) the interaction of the instrument and the same dummy to the first stage. The dependent variable in equation 3 is the inverse hyperbolic sine of the row label.

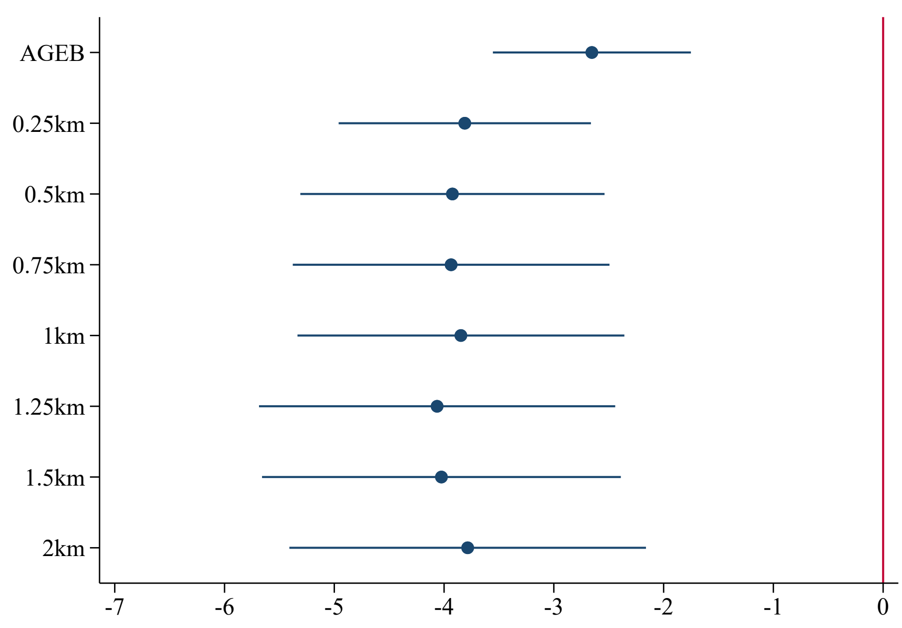


Figure A.11: Robustness: Alternative Neighborhood Definitions

Note: The figure displays the estimation of equation 3 using 2SLS with alternative neighborhood definitions. In row 1, the neighborhood is defined at the census tract level. In rows 2 to 8, a neighborhood is defined as the census tracts that are within the distance in the label of the census tract center.

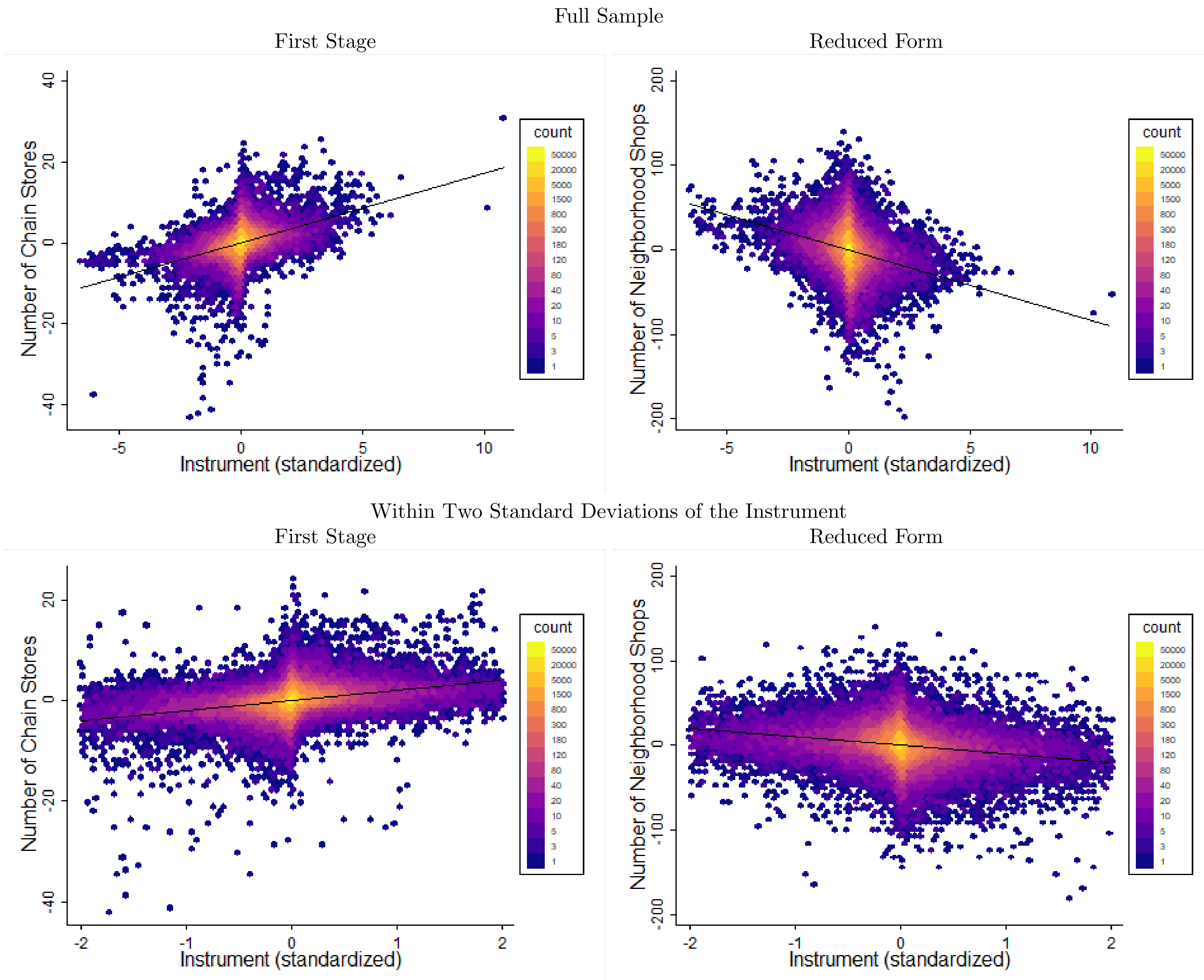


Figure A.12: Variation After Residualizing by Year-City and Neighborhood

Note: The figures display the variation in the data after residualizing by year-city and neighborhood.

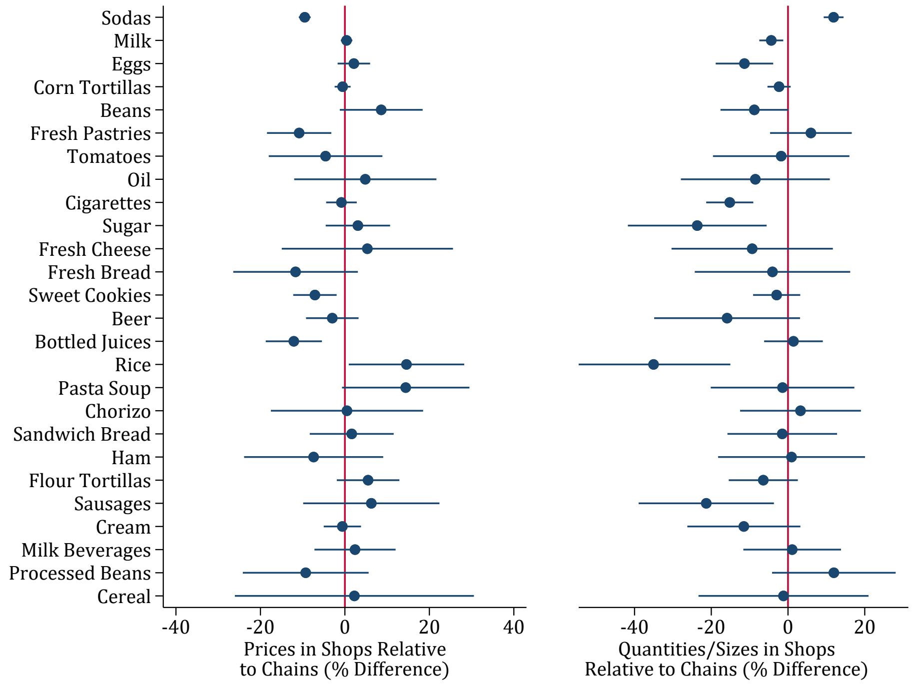


Figure A.13: Prices and Quantities/Sizes Differences between Chains and Shops

Note: The figure displays the differences in prices and quantities/sizes between purchases in Chains and Shops and the 95% confidence interval. The standard errors are clustered at the city level and the estimation includes household fixed effects. Prices are per unit; for example, sodas and other beverages are priced per liter, and beans, tomatoes, and rice are priced per kilogram.

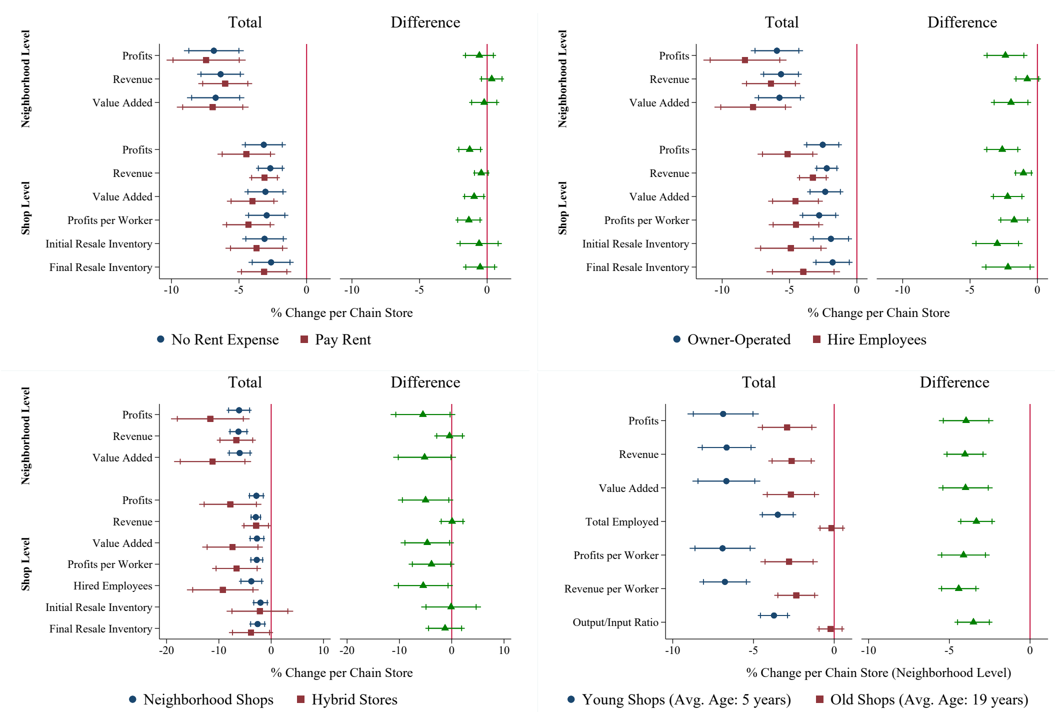


Figure A.14: Heterogeneity Controlling for Distance to Closest Convenience Chain

Note: The figure replicates Figures 5, 6, A.9, A.10 but controlling for the distance to the closest convenience chain.

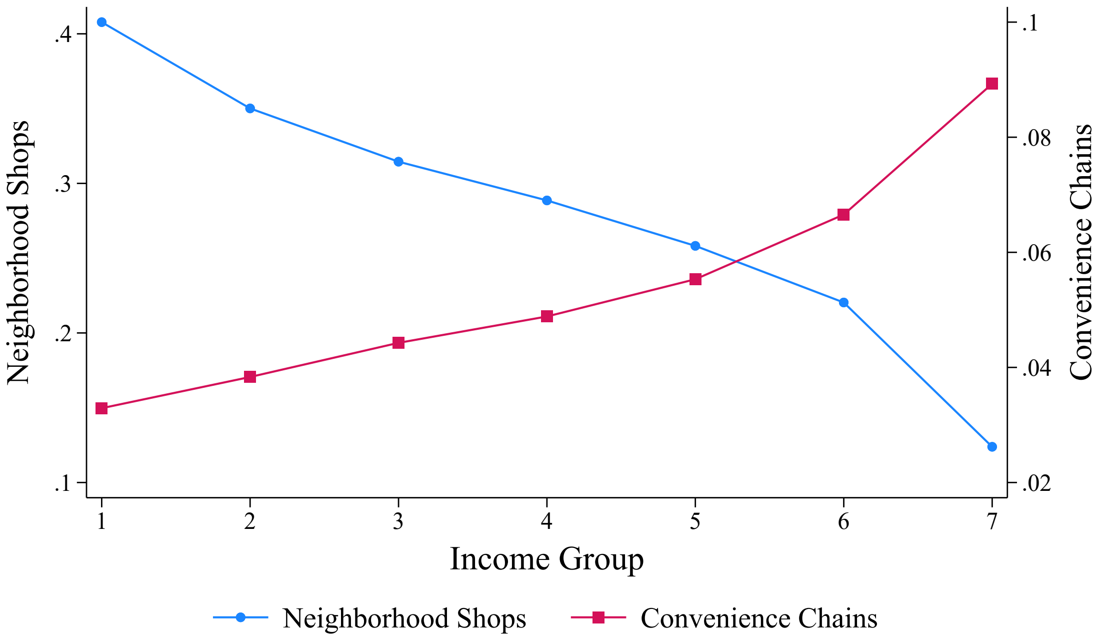


Figure A.15: Ex Post Market Shares by Income Group

Note: The sample includes 25,036 households living across 376 municipalities in census tracts where convenience chains are present (market share ≥0.5%) from retail transactions in ENIGH 2018.

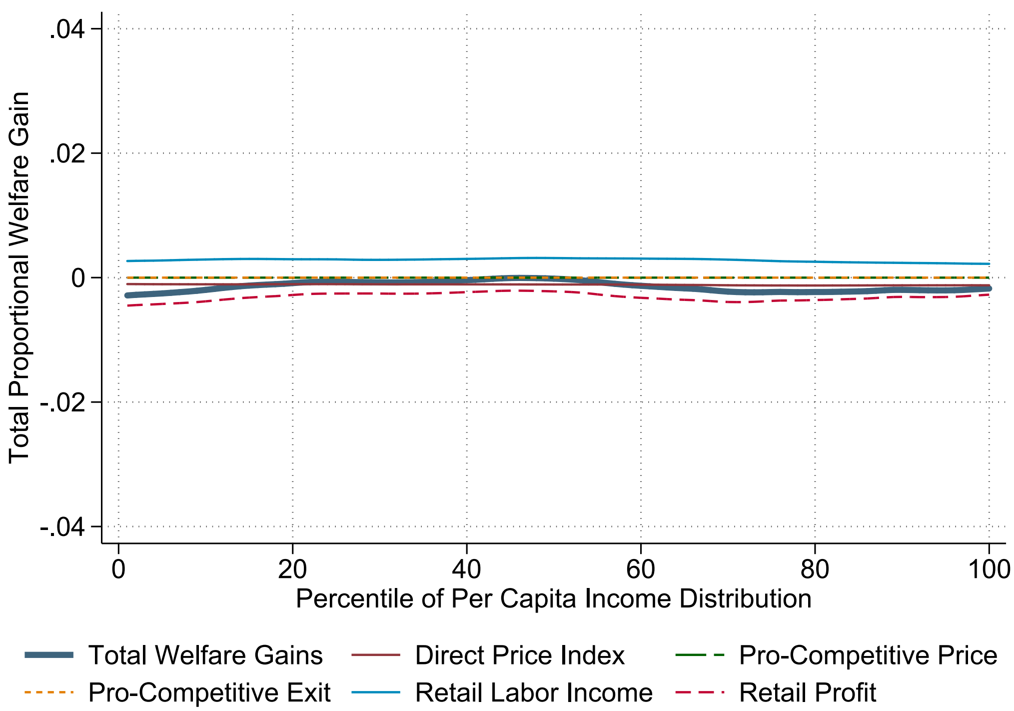
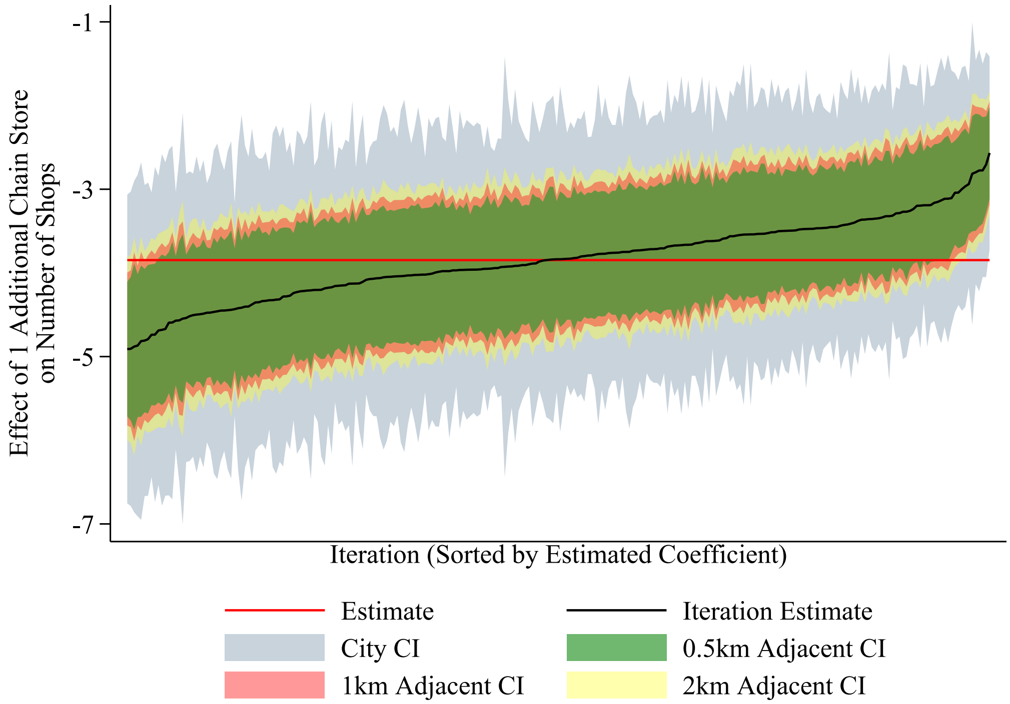


Figure A.16: Welfare Effects - First Order Approximation

Note: The graph displays the non-parametric plots of the effect of the expansion of chains and the reduction in the number of shops on household welfare using a first-order approximation based on observed price differences to estimate the cost of living effect. The quantification exercise is described in Online Appendix D and Section 6 . The plot corresponds to the average of 1,000 bootstraps described in the Online Appendix D.



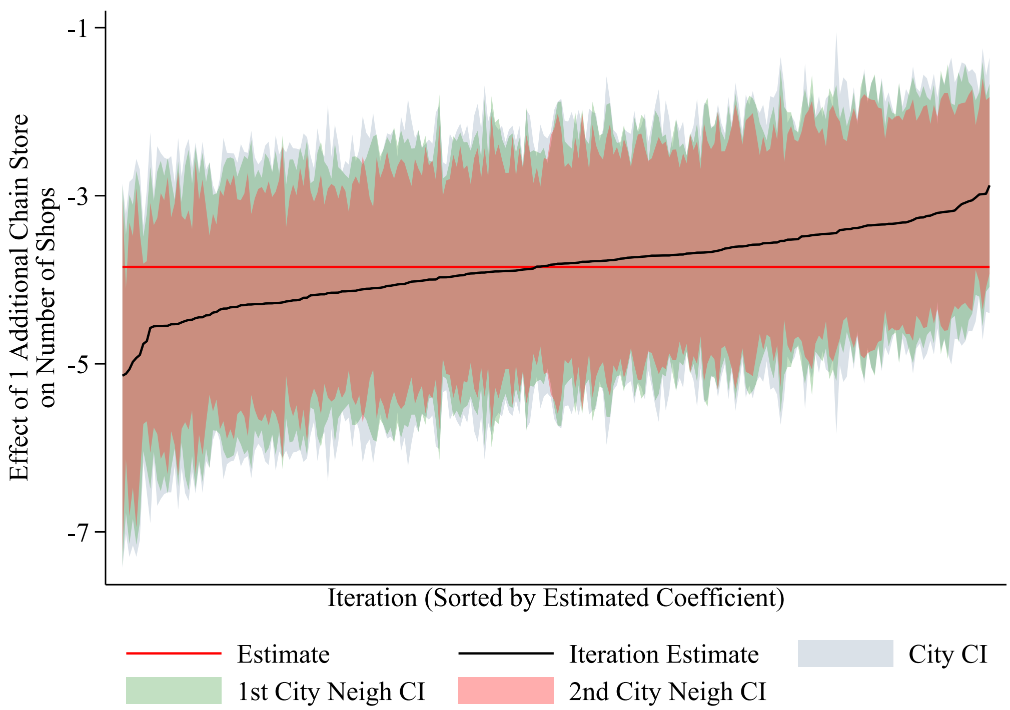


Figure A.17: Addressing Potential Spatial Correlation in Standard Errors

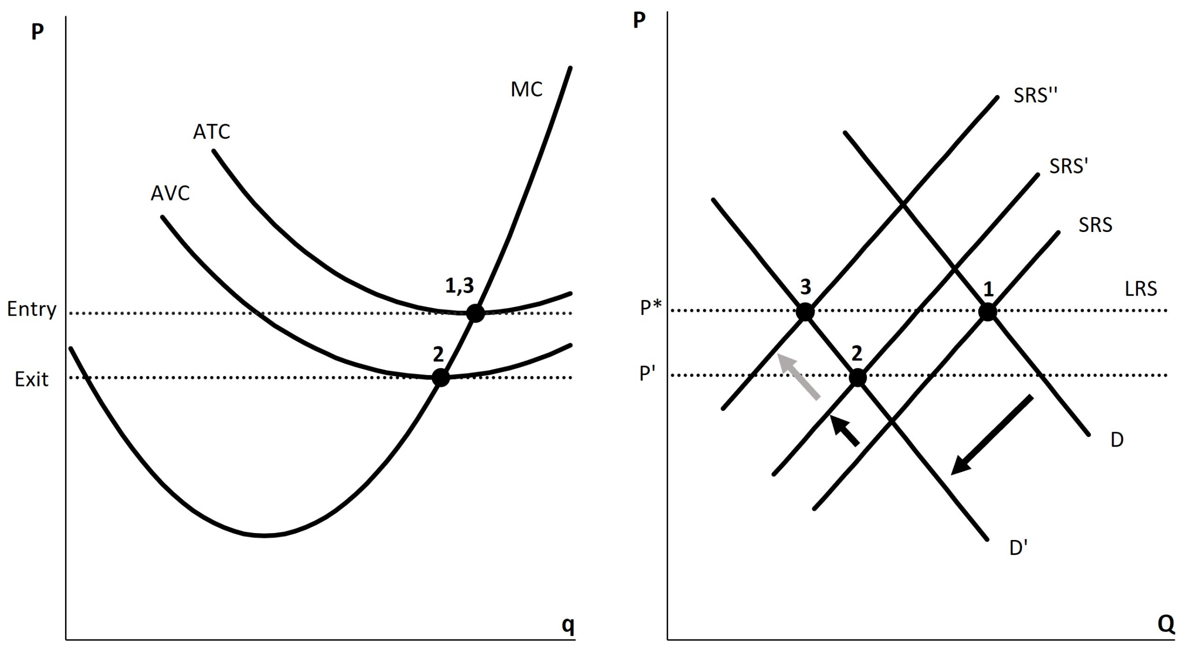
Note: The figure displays the estimation of Equation 3 using 2SLS. Each figure contains 250 estimations with a random sample of 5,000 markets. The figure on top displays standard errors clustered at the city level and standard errors accounting for the potential correlation of unobserved shocks across adjacent neighborhoods. The figure on the bottom includes standard errors that account for the potential correlation of unobserved shocks across adjacent cities. I use the technique proposed by Colella et al. (2019) to account for the potential spatial correlation of unobserved shocks and its companion statistical package *acreg*.

Online Appendix B: Model

This section presents a model of differentiated competition consistent with the adverse effect of the entry of chains on shops occurring mainly along the extensive margin and the decrease in shop entry driving the reduction in the number of shops.

Consider a competitive industry with many homogeneous firms (i.e., all shops in a given neighborhood), each facing sunk entry costs and standard u-shaped marginal and average costs. Assume free entry of firms and a high exogenous exit rate due to a fraction of them facing a sizable idiosyncratic shock, e.g., the owner's death.[21] I model the arrival of chains, an imperfect substitute, as a downward shift in industry-level demand for shops. Figure B.1 depicts the cost curves of a representative shop on the left side and the neighborhood-level supply and demand curves on the right side.

Before chains' entry (point 1), the equilibrium price is given by the intersection of the short-run supply (SRS) and demand curves, which is also equal to the minimum average total cost (ATC), inclusive of the sunk entry cost. At this price, potential entrants are indifferent about entering or not. Because the price is above average variable cost (AVC), incumbents have short-term economic profits. This equilibrium behaves as a steady state, with new firms replacing those that exit due to idiosyncratic shocks.[22]



Firm (Shop) Level | Industry (Neighborhood) Level

Figure B.1: Differentiated Competition with Entry Costs

Note: The figure on the left contains the marginal cost (MC), average variable cost (AVC), and average total cost (ATC) curves of a representative shop. The sunk entry cost drives the difference between the ATC and AVC. The figure on the right plots the transition from the long-term equilibrium (1) to a short-term equilibrium (2) caused by the entry of a differentiated competitor shifting the demand curve from D to D'. At (2), firms that face the idiosyncratic shocks exit, but new firms do not enter. This exit without replacement leads to a shift upward of the supply curve from SRS to SRS' and a new long-run equilibrium in (3).

Now suppose chains enter. Provided the resulting downward shift in demand is large relative to the sunk entry cost, the intersection of the new demand curve and the SRS curve will occur below the minimum

[21] This assumption is consistent with a 10% yearly exit rate.

[22] Firms that face the idiosyncratic shock exit, which shifts the short-run industry supply curve up, increases the equilibrium price, and makes entry profitable. Entry shifts the short-run supply curve back down until the potential entrants are indifferent between entering or not, and the price returns to its long-run equilibrium (ATC = MC).

AVC.[23] In this case, shops face short-term losses and begin to exit. This process shifts up the SRS curve until it intersects the demand at a price equal to the minimum AVC, point 2, where incumbents are indifferent between exiting or not. This new short-run equilibrium has a lower price, profits, and revenue.

Some shops exit due to their idiosyncratic shocks as time progresses, but new firms do not replace them because the price is below the minimum ATC. These exits without replacement gradually shift up the short-run supply curve until the price equals the minimum ATC (point 3). This new steady-state differs from the first (point 1) at the neighborhood level because it has lower profits and revenue. Provided the fraction of shops facing idiosyncratic shocks has not changed, fewer exits and entries will be in the new steady state because fewer shops exist.

In summary, the model predicts that there will be a reduction in the number of shops, a decrease in the number of entries, an ambiguous effect in the number of exits, and that the negative effects on shops' performance will concentrate on the extensive margin. With current assumptions, surviving shops are as well-off after the entry of chains. The model can be extended to allow heterogeneity in shops, for example, in their entry cost. This heterogeneity would lead to the long-run supply having a positive slope and chains' entry having a negative impact at the shop level.

[23] Alternatively, suppose the intersection of the new demand curve and the SRS curve occurs above the minimum AVC (not depicted). In that case, incumbents' profits decrease but not enough to incur short-term losses and exit.

Online Appendix C: Zeroth Stage

If chains exploit economies of scale arising from stores in nearby cities sharing distribution, monitoring, marketing, and overhead costs, chains would open stores in cities close to each other. To quantify the importance of economies of scale I estimate the relationship between the number of chain stores that chain f has in cities adjacent to city c at time $t-1$ and the number of chain stores that f has in city c at time t. I interpret the coefficient of interest, β, as a measure of economies of scale.

$$\#Stores_{f,c,t} = \eta_{f,t} + \mu_{c,t} + \zeta_{f,c} + \beta \#StoresNearbyTowns_{f,c,t-1} + \epsilon_{f,c,t} \quad \text{(C.1)}$$

Table C.1: Same-Chain Economies of Scale

	Dependent Variable: # of Chain Stores in City								
Nearby Cities:	2nd Degree Adjacent Cities			Adjacent Cities			3rd Degree Adjacent Cities		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Number of Stores Nearby	0.064***	0.064***	0.056***	0.157***	0.157***	0.134***	0.031***	0.031***	0.027***
Cities (same chain)$_{t-1}$	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.00)	(0.00)	(0.00)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Number of Neighborhood		0.000			0.000			0.000	
Shops Nearby Cities$_{t-1}$		(0.00)			(0.00)			(0.00)	
		[0.9760]			[0.5667]			[0.7948]	
Sample Size		335,240			335,240			335,240	
Clustered SE	City	City	City	City	City	City	City	City	City
Year, City, & Firm FE	Y	Y		Y	Y		Y	Y	
Firm x City FE			Y			Y			Y
Year x Mun FE			Y			Y			Y
Year x Firm FE			Y			Y			Y
R-squared	0.152	0.152	0.809	0.174	0.174	0.813	0.126	0.126	0.802
Within R-squared	0.089	0.089	0.094	0.112	0.112	0.115	0.061	0.061	0.063

Note: The table displays the estimation of equation C.1. For columns 1-4, Nearby Towns are the adjacent towns and those adjacent to these, for columns 5-6 Nearby Towns are the adjacent towns, and for columns 7-8 Nearby Towns are the adjacent towns, those adjacent to these, and those adjacent to the adjacent towns.

Across all specifications in Table C.1, there is strong evidence of economies of scale: the number of same-chain stores in cities nearby is positively correlated. Columns 1-3 use 2^{nd} degree neighbors (adjacent cities and cities adjacent to these), columns 4-6 use 1^{st} degree neighbors, and columns 7-9 use 3^{rd} degree neighbors. Economies of scale matter: 18 additional same-chain stores in nearby cities translate to one more same-chain store in the city–accounting for 9% of the variation in the number of stores each chain has in a city.[24]

Table C.1 documented the existence and importance of economies of scale for the expansion of chains. The following analysis tests whether these economies of scale are indeed firm-specific. If all chains enter the same cities at the same time, this would be likely driven by city characteristics and not by firm-level

[24] The 9% is obtained by computing the within R-squared. It is the R-squared after demeaning each variable with respect to the fixed effects.

Table C.2: Cross-Chain Economies of Scale

	Dependent Variable: # of Chains Stores in City						
Nearby Cities:	2nd Degree			Adjacent Cities		3rd Degree	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Number of Stores Nearby Cities	-0.001***	-0.001***	-0.002***	-0.002***	-0.004***	0.000***	-0.001***
(different chain)$_{t-1}$	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Sample Size	11,062,920			11,062,920		11,062,920	
Clustered SE	City	City	City	City	City	City	City
Year, City, & Firmj FE	Y	Y		Y		Y	
Firm k FE		Y		Y		Y	
Firm j x City & Firm k x City FE			Y		Y		Y
Firm j x Year & Firm k x Year FE			Y		Y		Y
Year x Mun FE			Y		Y		Y
R-squared	0.070	0.070	0.789	0.070	0.789	0.070	0.789
Within R-squared	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: The table displays the estimation of equation C.2. For columns 1-3, Nearby Towns are the adjacent towns and those adjacent to these, for columns 4-5 Nearby Towns are the adjacent, and for columns 6-7 Nearby Towns are the adjacent towns, those adjacent to these, and those adjacent to the adjacent towns.

economies of scale. The following equation tests for cross-firm economies of scale, which should not exist if economies of scale are indeed firm-specific and driven by cost-sharing within firms. The coefficient of interest, β, estimates the relationship between the number of stores chain g has in cities nearby to city c at time t and the number of stores that chain f (a competitor) has in city c at time t after controlling for firm(f)-time, firm(g)-time, city-time, firm(f)-city, and firm(g)-city fixed effects.

$$\#Stores_{f,c,t} = \eta_{f,t} + \mu_{c,t} + \zeta_{f,c} + \gamma_{g,t} + \delta_{g,c} + \beta\#StoresNearbyTowns_{g,c,t-1} + \epsilon_{f,c,t} \tag{C.2}$$

Economies of scale are firm-specific: the positive correlation in Table C.1 dissipates when using the number of different-chain stores (competitors) in nearby cities, and the number of competitors in nearby cities accounts for less than 0.001% of the variation in the number of stores each chain has in a city. The results are in Table C.2. Across all specifications, there is no evidence of cross-firm economies of scale. Moreover, there is a small pro-competitive effect: a negative relationship between the number of stores a competitor g has in towns adjacent to town c and the number of stores chain f has in town c.

Online Appendix D: Welfare Quantification

I use the framework and code of Atkin, Faber and Gonzalez-Navarro (2018), AFG2018, to decompose the welfare effects of the expansion of chains into three effects on the household cost of living and two effects on nominal household incomes.[25] The cost of living effects are the effect on shops' prices (procompetitive price effect), the effect from the reduction in the number of shops (procompetitive exit effect), and the direct price index effect that includes the gains from being able to purchase in convenience chains, such as differences in prices, variety, and store amenities. The effects on nominal household incomes are the effect on employment and wages in the retail segment and the retail profits of owners.

Similarly to AFG2018, I estimate the welfare effects using the 24,310 households living across 829 municipalities from ENIGH 2006, 2008, 2014, and 2018 in census tracts without convenience chains based on the Economic Censuses from 2004, 2009, 2014, and 2019. The main adjustment is that I do not have a separate effect for traditional and modern sectors because all shops are traditional. The inputs required for the estimation are the effect on shops' prices (overall, food, and non-food), the price gap between chains and shops (overall, food, and non-food), ex ante and ex post market shares (by 12 product groups, and 7 household income groups), effect on the number of shops, the elasticity of substitution between chains and shops (overall and by food and non-food and rich and poor households), effect on shop owners' profits, effect on wages in shops and chains, and effect on employment in shops and chains.

The remainder of this appendix is divided into three sections. The first section discusses estimating the elasticity of substitution between chains and shops and the cost of living effect, the second describes how the estimated moments enter the quantification, and the third presents the quantification results.

I Cost of Living Effect

I follow AFG2018 and estimate the cost of living effect using two alternative methodologies. The first is a first-order approximation based on observed price differences, and the second is an exact estimation under a CES demand. The main difference in interpretation is that the CES alternative captures the effects on welfare from changes in variety and amenities, while the first-order approximation ignores these because, basically, it assumes that chains and shops always exist. In the first-order approximation, the direct price index effect is essentially multiplying the post-entry shares of convenience chains by their price difference with shops, and the procompetitive effect is multiplying the post-entry share of shops by the price reduction in shops.

The CES demand is a three-tiered system. The top tier is a Cobb-Douglas over product groups. In the middle tier, consumers have CES preferences over purchasing in neighborhood shops or convenience chains, and the final tier has individual preferences over the specific product within the product group. I recover the elasticity of substitution between chains and shops by estimating a regression of log budget shares on log store-specific price indices, as in AFG2018, where the elasticity of substitution between chains and shops is one minus the estimate in Table D.1.

As discussed in AFG2018, the estimate of this regression may suffer from endogeneity even when including product group by income group by city and store type by product group fixed effects because demand shocks can affect both store-level market shares and store-level price indices. Similarly to AFG2018, I instrument log store-specific price indices using the leave-one-out national and regional indexes. Columns 3 to 14 present

[25] I do not include as a potential channel the indirect effect on other sources of household income from other sectors, such as manufacturing and agriculture.

Table D.1: Elasticity of Substitution between Chains and Shops

	Dependent Variable: Log Budget Shares													
	Mean Prices OLS	Median Prices OLS	Mean Prices National IV	Median Prices National IV	Mean Prices National IV	Median Prices National IV	Mean Prices National IV	Median Prices National IV	Mean Prices Regional IV	Median Prices Regional IV	Mean Prices Regional IV	Median Prices Regional IV	Mean Prices Regional IV	Median Prices Regional IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Panel A														
Log(store price index)	-0.383***	-0.361***	-0.947***	-1.091***	-1.307***	-1.509***	-1.459***	-1.650***	-0.960***	-1.107***	-1.347***	-1.585***	-1.485***	-1.704***
	(0.0429)	(0.0426)	(0.153)	(0.183)	(0.183)	(0.216)	(0.196)	(0.236)	(0.205)	(0.251)	(0.205)	(0.257)	(0.223)	(0.282)
KPF Statistic			183.95	153.78	179.60	132.37	154.35	121.59	124.98	114.46	149.35	115.66	134.38	102.78
Panel B														
Log(store price index) x poor x food	-0.434***	-0.415***	-1.517***	-1.613***	-2.044***	-2.105***	-2.252***	-2.262***	-1.316***	-1.453***	-1.782***	-1.954***	-1.931***	-2.069***
	(0.0691)	(0.0701)	(0.224)	(0.234)	(0.246)	(0.254)	(0.266)	(0.278)	(0.291)	(0.326)	(0.292)	(0.328)	(0.315)	(0.355)
Log(store price index) x rich x food	-0.496***	-0.482***	-1.436***	-1.509***	-1.916***	-1.968***	-2.099***	-2.105***	-1.279***	-1.390***	-1.703***	-1.854***	-1.834***	-1.954***
	(0.0672)	(0.0651)	(0.204)	(0.214)	(0.223)	(0.234)	(0.245)	(0.258)	(0.263)	(0.296)	(0.268)	(0.304)	(0.290)	(0.329)
Log(store price index) x poor x nonfood	-0.305***	-0.292***	-1.191***	-1.405***	-1.628***	-1.827***	-1.812***	-1.971***	-1.031***	-1.266***	-1.440***	-1.726***	-1.574***	-1.827***
	(0.0422)	(0.0439)	(0.182)	(0.210)	(0.203)	(0.230)	(0.220)	(0.252)	(0.234)	(0.286)	(0.239)	(0.295)	(0.258)	(0.319)
Log(store price index) x rich x nonfood	-0.319***	-0.258***	-1.215***	-1.253***	-1.712***	-1.765***	-1.907***	-1.923***	-1.046***	-1.098***	-1.527***	-1.662***	-1.675***	-1.788***
	(0.0490)	(0.0521)	(0.183)	(0.199)	(0.214)	(0.227)	(0.235)	(0.251)	(0.232)	(0.269)	(0.236)	(0.275)	(0.260)	(0.305)
KPF Statistic			50.03	38.84	48.15	34.28	41.62	32.47	29.10	27.04	32.15	25.97	29.11	23.74
Observations	1,875,160	1,875,160	1,874,726	1,874,726	1,874,642	1,874,642	1,874,566	1,874,566	1,872,470	1,872,470	1,872,387	1,872,387	1,872,311	1,872,311
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Product group x income group x city FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Store type x product group FE	Y	Y	Y	Y	Y	Y			Y	Y	Y	Y		
Store type x city FE					Y	Y					Y	Y		
Store type x product group x city FE							Y	Y					Y	Y

Note: The table displays the relationship between log budget shares and log store-specific price indices. The coefficient corresponds to one minus the elasticity of substitution between chains and shops. The data are from ENIGH 2012, 2014, 2016, and 2018. The dependent variables are log expenditure shares by municipality, year, product group, and income group. The independent variable is a log store-specific price indices at the municipality, year, product group, and income group recovered from the store by product group by income group by city by year fixed effect of regression of budget share-weighted log prices on this fixed effect and a product by income group by city by year fixed effect. Standard errors are clustered at the municipality level.

estimates using these instruments. The average elasticities range between 1.95 and 2.70. The estimates are smaller than those of the elasticity of substitution between domestic and foreign supermarkets in AFG2018. The smaller elasticity of substitution between chains and shops is consistent with differences between these being more significant than differences between domestic and foreign supermarkets. In particular, the broader differentiation between OXXO and Abarrotes Lupita relative to Bodega Aurrera and Soriana is likely the driver behind the smaller elasticity of substitution between chains and shops.[26]

The main disadvantage of using ENIGH data is that transactions are disaggregated up to the establishment type level. It is observable if the households purchased in a chain or a shop, but not in which chain. Hence, the estimated elasticity of substitution is between chains and shops as a group. A related concern is that the first stage in the IV specifications may be weak because of not using the same chain price indices and using the overall price indices of chains. However, this does not seem to be an issue because the first stage is strong in all specifications (Kleibergen-Paap Wald rk F statistic ranges from 23 to 184).

II Combining Estimated Moments for the Quantification

The inputs required for the estimation are the effect on shops' prices (overall, food, and non-food), the price gap between chains and shops (overall, food, and non-food), ex ante and ex post market shares (by 12 product groups, and 7 household income groups), effect on the number of shops, the elasticity of substitution between chains and shops (overall and by food and non-food and rich and poor households), effect on shop owners' profits, effect on wages in shops and chains, and effect on employment in shops and chains. This section details how each of the estimated moments enters the quantification.

The effect of chains on shops' prices is null (Table A.6). I use a price gap between chains and shops of 3.9% overall, 3.9% for food, and 1% for non-food (Table A.4).[27] The ex post market shares are from 25,036 households living across 376 municipalities in census tracts with convenience chain presence (market share $\geq$0.5%) from ENIGH 2018 (Figure A.15). I use the largest estimates for the elasticity of substitution (Column 14 of Table D.1), because they render the smallest (most conservative) effects on procompetitive exit and direct price index.

I use a 10.69% decline in the number of neighborhood shops. This is the estimated reduction of 3.85 shops per convenience chain (Table 2) times 3.98 chain stores on average per neighborhood, divided by 143 neighborhood shops on average per neighborhood. This implies a reduction of 100% of profits for 10.69% of shop owners. For the remaining shop owners, the reduction in profits is 5.8%, 1.46% for each additional convenience chain store times 3.98 chain stores in the neighborhood. I cannot identify precisely who are the shop owners in the ENIGH, because it includes only up to four digits of the SCIAN code. According to the 2019 Economic Census, 62% of the establishments in the 4611 SCIAN code are neighborhood shops. Hence, I apply the effect to all owners of uni-personal establishments in 4611 (37.5% of owners in 4611) and to a random 60% of the owners of establishments with 2 to 5 people employed (41.6% of owners in 4611), matching the 62% share of shops out of the establishments in 4611 SCIAN code.

In 1999, the average number of jobs in a neighborhood offered by the segment of chains and shops was small, just 12.87 (.09 employees per shop x 143 shops per neighborhood). With an average of 3.98 chains per neighborhood, jobs increase by 30, more than 200%. This is a large percentage increase, but it is in a very small part of the labor force (only 0.5% of employees in Mexico are shop employees). Hence, the overall

[26] Walmart has over 2,000 Bodega Aurrera stores in Mexico, making it the modal foreign supermarket.

[27] I use the same price gap overall and for food, because ENIGH does not include size/quantity for non-food products. Hence using all products but controlling for size/quantity renders the same estimate as only using food.

Table D.2: Quantification Estimates

	A. Exact under CES approach				
	Total Effect	Direct Price Index Effect	Procompetitive Exit Effect	Retail Labor Income Effect	Retail Profit Effect
	(1)	(2)	(3)	(4)	(5)
Average Effect	0.0046	0.0268	-0.022	0.0028	-0.0031
	(0.00020)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
95% Bootstrap C.I.	[-0.005 , 0.013]	[0.022 , 0.034]	[-0.034 , -0.013]	[0.002 , 0.004]	[-0.005 , -0.001]
Min-Max Bootstrap	[-0.010 , 0.022]	[0.019 , 0.047]	[-0.043 , -0.004]	[0.001 , 0.005]	[-0.007 , -0.001]
Proportion negative	0.156	0	1	0	1
Obs. (households)	24,310	24,310	24,310	24,310	24,310
Number of Cities	829	829	829	829	829
	B. First-Order Approach				
	Total Effect	Direct Price Index Effect	Procompetitive Exit Effect	Retail Labor Income Effect	Retail Profit Effect
	(1)	(2)	(3)	(4)	(5)
Average Effect	-0.0014	-0.0011	0	0.0028	-0.0031
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
95% Bootstrap C.I.	[-0.004 , 0.001]	[-0.001 , -0.001]	[0.000 , 0.000]	[0.002 , 0.004]	[-0.005 , -0.001]
Min-Max Bootstrap	[-0.005 , 0.002]	[-0.002 , -0.001]	[0.000 , 0.000]	[0.001 , 0.005]	[-0.007 , -0.001]
Proportion negative	0.912	1	0	0	1
Obs. (households)	24,310	24,310	24,310	24,310	24,310
Number of Cities	829	829	829	829	829

Note: The table reports the effect of the expansion of chains and the reduction in the number of shops on household welfare from the quantification exercise described in Online Appendix D and Section 6 . Panel A estimates the cost of living effect using a CES demand system, and panel B uses the first-order approximation. The average effect and standard errors are the averages across the 1,000 bootstraps. The confidence intervals in brackets are the 2.5 and 97.5 percentiles of the bootstraps.

effect on employment is 1.15%. Chains do not affect the wages of shops' employees, but because they pay more to their employees, the average wage in the segment (shops + chains) increases by 4%, 1% per chain store (Table A.5).

The quantification estimates are the average of 1,000 bootstrap iterations. In each bootstrap, each effect is drawn from a normal distribution with the point estimate as a mean and the standard error as the standard deviation. The households being affected by effects that only affect subgroups of households are also selected randomly in each iteration. For example, 10.69% of shop owners who lose 100% of their retail income are selected randomly in each iteration.

III Results

In the CES specification, the procompetitive exit and the direct price index are the largest contributors to the overall welfare effect. Since convenience chains are not cheaper, the direct price index effect captures the gains from varieties and amenities of purchasing in chains, which include parking, air conditioning, flexible hours (24/7), and acceptance of electronic payment methods. The rich appreciate these amenities the most; hence, the gain from the direct price index for the rich is more than 20% larger, reaching 3.2%.

On the other hand, the procompetitive exit effect is the loss of welfare due to the reduced number of neighborhood shops. It is the largest for the poor (2.9%) and decreases throughout the income distribution, it being half the magnitude for the rich (1.5%). This is driven by poorer households, who are more cash and credit-constrained, appreciating shops and their amenities the most, such as informal credit, relationships with the owner, closeness to home, broader and tailored product mix, and ripeness of products.

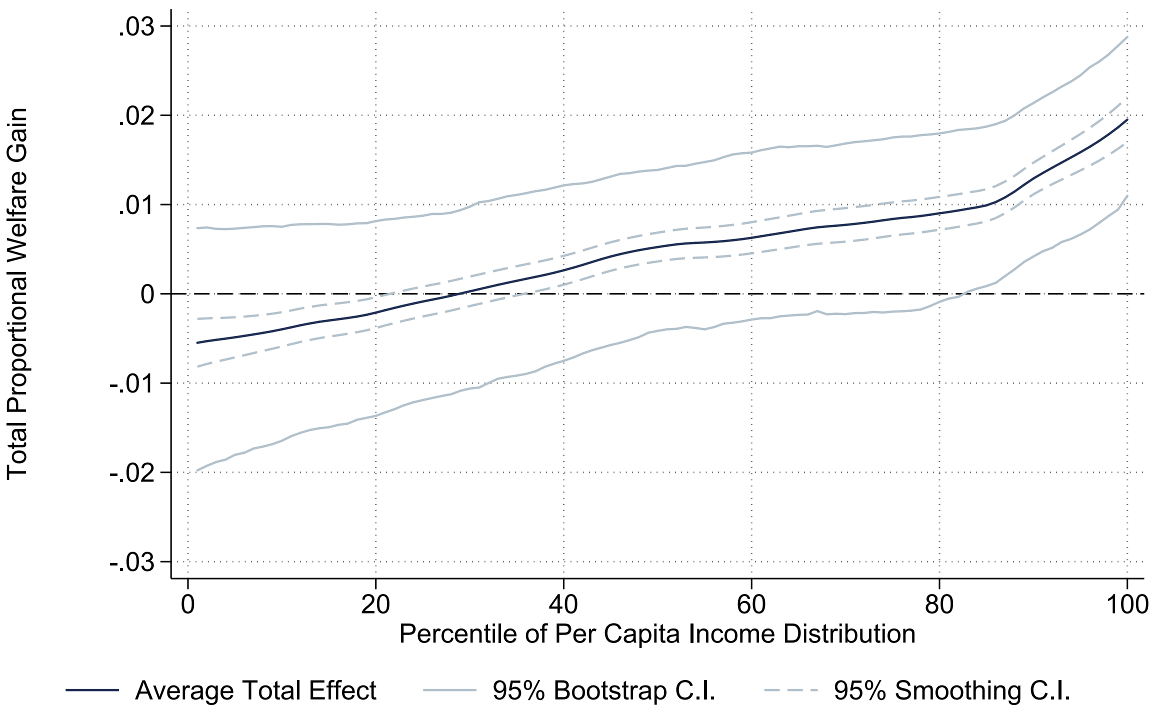


Figure D.1: Welfare Effects

Note: The graph displays the non-parametric plots of the effect of the expansion of chains and the reduction in the number of shops on household welfare using a CES demand system to estimate the cost of living effect. The quantification exercise is described in the Online Appendix D and Section 6 . The solid line corresponds to the average of 1,000 bootstraps described in the Online Appendix D, the tighter dashed lines are the average of the 95 percent confidence intervals of the polynomial smoothing, and the solid gray lines are the 2.5 and 97.5 percentiles of the bootstraps.

Consistent with the main driver of the welfare effect being the amenities no longer available at shops and those now available at chains, the first-order approximation has a zero procompetitive effect because the effect on shops' prices is zero. The direct price index effect becomes negative (Figure A.16), because chains are slightly more expensive than shops, and without taking into account amenities replacing shops with chains is just a price increase. In summary, the direct price index effect in the CES model is positive and large because it considers the amenities and varieties offered at chains, while the first-order one is negative because it does not.

The income effects mostly cancel each other out because labor income from new jobs at convenience chains compensates for lost income from shop owners' profits. The expansion of chains leads to 10.69% fewer shops. Hence these households lose this source of income. Moreover, for the shops that do not close, profits decline by 5.8%. However, chains also create a new source of income for households by creating jobs. On average, the decrease in jobs in shops (including owners) and the increase in jobs in chains wash out (Table A.5). In the quantification, the loss in retail profits of shop owners is compensated by the increase in retail labor income from the job creation of chains. However, because shop owners' profits are higher than wages at convenience chains, the negative effect of the retail profit (0.31%) is 10% larger than the positive retail labor income effect (2.8%).[28]

In summary, the cost of living effect is the main driver of the welfare effects because the income channels have a smaller magnitude and mostly cancel each other out. The richest households are the ones who appreciate the least the existence of shops and value the most chains' entry, and vice versa for the poor, leading to a welfare gain of 1.6% for the richest and a welfare loss of 0.5% for the poorest.

[28] Based on the 2019 Economic Census, an average shop makes 9,500 MXN of monthly profits and 1.5 family members work there, hence 6,300 MXN per person. An average production, sales, and services employee in a convenience store makes 6,200 MXN minus taxes and social security.