Preliminary Evidence of Surviving Competition:

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 chains' 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 16%. Consistent with the theoretical framework, this reduction is not driven by an increase in shop exit but by a decrease in shop entry. 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. I present evidence consistent with shops surviving by exploiting comparative advantages stemming from being small and owner-operated, such as lower agency costs, building relationships with the community, and offering informal credit.

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I Introduction

In developing countries, a stunning 214 million microenterprises account for 84% of all firms, 40% of employment, and 21% of value-added.[1] 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 lead to firms becoming unprofitable, such as increased labor or other inputs cost, 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 specific size.[2] 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*.[3] Across the globe, shops share common characteristics, such as being small and primarily owner-operated, offering a wide variety of food and drinks, and their neighbors being their primary customers.

[1] Source: SME Finance Forum (2019)

[2] For example, India's Annual Survey of Industries covers firms with at least ten 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).

[3] Sources: Economic Times (2019); Philstar (2017)

I study the context of Mexico, where shops are vital to the economy. They represent one out of every eight firms, 4% of total employment, and they have the largest market share in the food and beverages industry, 31%.[4]

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 a direct competitor to shops because they significantly overlap in their product offering, 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.

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.[5] I link this 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 among 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

[4]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%.

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

cost-sharing in distribution, transportation, marketing, overhead, and other costs reduces chains' average cost 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. And second, different from 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 is growing 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. And 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. The empirical section discusses other potential concerns in more detail and the analyses 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 4.5, implying that an expansion from zero to the average number of chain stores in a neighborhood (6.4) reduces the number of shops by 16%. The number of exits of shops does not increase, making the 21% 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 4%. Those who continue to purchase in shops do so 7% 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 sweet bread, 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.

Why do shops survive? I find evidence consistent with shops adjusting to competition and leveraging their comparative advantages. Surviving shops' productivity, measured as an output-input ratio, is unaffected by chains because shops respond to the decrease in revenue with a reduction in purchases and inventories. Moreover, shops less affected by chains are smaller and owner-operated. The estimates presented in the Discussion section are consistent with small and owner-operated shops having comparative advantages in facing lower agency costs, building relationships with their customers, 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 specialize 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. Moreover, the expansion of chains increases neighbors' purchases and the number of goods purchased using informal credit in shops. 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 results are consistent with a standard competitive model with differentiated competition between chains and shops presented in Section III. The model highlights economic mechanisms driving the asymmetry between shop entry and exit as the shop industry transitions from a steady state without chains to a steady state with them. The model presents this transition at the shop and industry levels to illustrate why the adverse effects on shops' performance concentrate along the extensive margin.

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 twenty 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.[6] Other papers in this literature include Bergquist and Dinerstein (2020) that 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

[6] 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)).

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. I present the model of differentiated competition in Section III. In Section IV, 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 V presents the empirical strategy and discusses potential concerns about the instrument's validity. In Section VI, I present the main results. In Section VII, I discuss the heterogeneity of the effects on shops and potential consumer welfare implications across the income distribution. Section VIII includes ample robustness checks for alternative instrument specifications, including sets of controls, and alternative standard errors. The last section concludes.

II Background

One out of ten firms and one out 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' house.[7] 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 also offer products that they make themselves (e.g., bread, sandwiches, pastries) or that they 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

[7]Sources for this and next paragraph: Economic Census (2019); COFECE (2020)

10 people, and stock between 300 and 800 SKUs. Even though chains and shops are often within a couple of meters, chains are in high-traffic locations next to wide streets.[8] Chains are perceived as very successful. In particular, the largest of them, OXXO, is perceived as the most successful food and beverages retailer in the country (above Walmart Mexico).[9] OXXO's annual sales per squared meter are 89,500 MXN, exceeding Walmart Mexico's 88,800 MXN,[10] 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%). Even though large producers deliver their products directly to both chains and shops, one of the keys to chains' success is their in-house logistics operations with distribution centers around the country that facilitate the distribution to each store in the chain of fruits, vegetables, liquor, medicines, cellphones, party supplies, among other products.[9]

Chains are a direct competitor 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.[11] However, chains could have a limited effect on shops because shops may have comparative advantages in building relationships with consumers, tailoring their product offering, offering informal credit to the neighbors, and providing similar prices.[12]

III Model

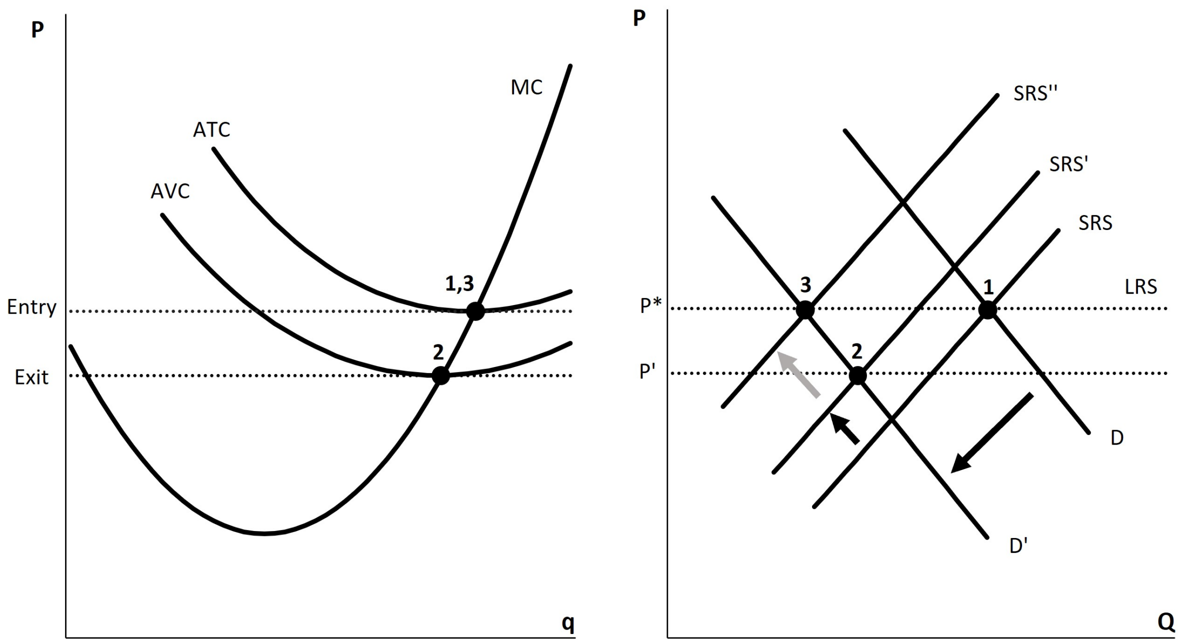
This section presents a model of differentiated competition consistent with the adverse effect of the entry of chains on shops occurring mainly along the extensive margin and the decrease in shop entry driving the reduction in the number of shops.

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

[8] Source: Milenio (2016); El Universal (2015)
[9] Source: El Financiero (2014)
[10] Source: El Financiero (2020)
[11] Source: El Universal (2017); El Universal (2015); El Financiero (2018)
[12] Source: Gonzalez Sanchez and Gaytán (2015); Milenio (2016)

facing a sizable idiosyncratic shock, e.g., the owner's death.[13] I model the arrival of chains, an imperfect substitute, as a downward shift in industry-level demand for shops. Figure 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.[14]



Firm (Shop) Level

Industry (Neighborhood) Level

Figure 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

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

[14]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).

will occur below the minimum AVC.[15] 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.

Five sets of estimates map directly to the model predictions. First, the decrease in the number of shops, represented by the distance between the steady-state before chains (point 1) and the steady-state after chains (point 3), is 16%. Second, the total effect on shop entry has two components with the same sign. The first is the lack of entries between the short-run equilibrium (point 2) and the new steady-state (point 3), and the second is the effect of moving from the steady-state without chains (point 1) to the steady-state with chains (point 3), where there are fewer shops and less entry and exit. The net of these two effects is a decline in shop entries by 21%. Third, the total impact on shop exit has two components but opposite signs. The first is the exits caused by chains' entry making some shops unprofitable (moving from point 1 to 2), and the second is the effect of moving from the steady-state without chains (point 1) to the steady-state with chains (point 3), where there are fewer shops and less entry and exit. The latter effect dominates the former, and the net effect of chains is a decrease in the number of shop exits by 8%. Fourth, The reduction in profits at the neighborhood level is 26%, represented by the distance between points 1 and 3 at the industry level times the vertical distance between point 3 and the AVC at the shop level. And fifth, the negative effect on profits at the shop level is less than a third of that at the industry level, 7%, because the reduction in the number of shops compensates for the adverse impact of chains.[16]

[15] 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.

[16] 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.

IV 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,[17] 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. For 2006, it contained responses from little more than twenty thousand households, and 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 has 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. I draw a buffer of 1km from the center of each

[17] Include both formal and informal firms without minimum size requirements.

AGEB. I define a neighborhood as the union of AGEBs that overlap with each buffer.[18] On average, there are 12 AGEBs in each neighborhood, 370 blocks, 30,000 people, 68 shops, and five chain stores. The robustness section shows results using alternative definitions of neighborhoods created with different 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 one 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.3 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 its size, specifically dividing by the square root of its 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.

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.

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

There are stark differences between shops and chains. On average, chain stores, relative to shops, have thirty times the revenue, twenty-five times the profits, four times the employees, six times the profits per employee, and seven times the revenue per employee. Chains are 2-5

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

Table 1: Summary Statistics Shops and Chains

	Shops	Chain Stores
Number	1,787,952	42,101
Annual Profits (000's MXN)	67	1,689
Annual Revenue (000's MXN)	251	10,098
Expenses (000's MXN)	183	8468
Value Added (000's MXN)	69	2,027
Total Employed	1.8	6.4
Profits per Worker (000's MXN)	40	329
Revenue per Worker (000's MXN)	145	2,111
Initial Resale Inventory (000's MXN)	11	514
Final Resale Inventory (000's MXN)	12	679
Fixed Assets (000's MXN)	66	1,928
Publicity (000's MXN)	0.1	32
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

times larger in squared 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.[19] Eighty-five percent of households purchase at least once a week in shops. The probability of buying in a chain is significantly lower, 15%. 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. The shops' exit rate from one census to the next is 40%, implying a 10% annual exit rate. This exit rate is similar to the average exit rate of microenterprises in other developing countries, 8.3% (McKenzie and Paffhausen, 2019). For chains, the yearly exit rate is below 3%.

Shops and chains have a significant overlap in their product offering. As Figure 2 displays, the five most popular products for shops (sodas, milk, eggs, tortillas, and bread), which represent almost half of their revenue, are also available and among the 12 most popular food products in chains. A limitation of the consumption data is that it does 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.4 presents

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

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.

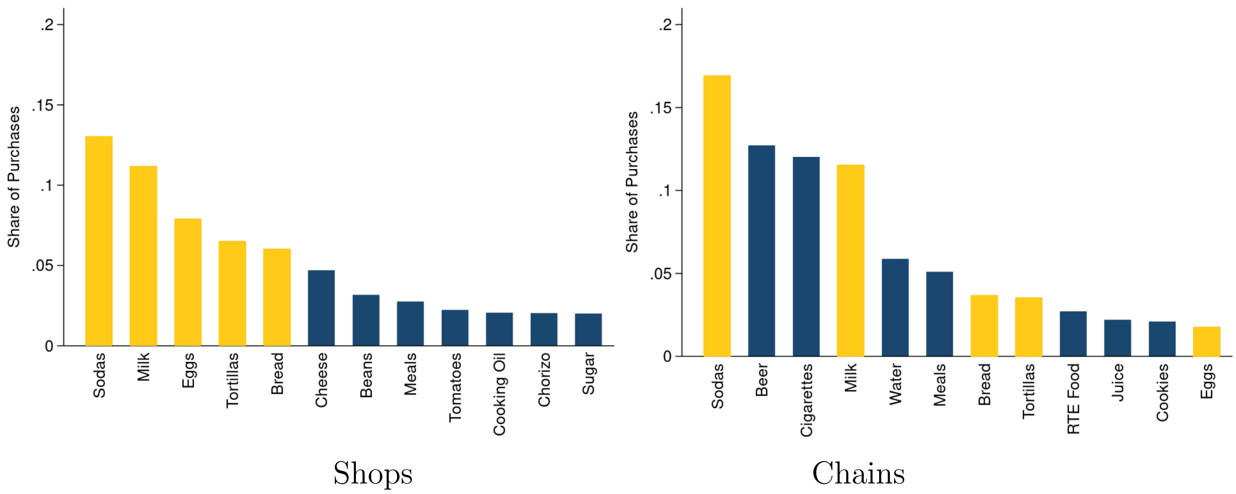


Figure 2: Share of Store Sales for Top 12 Products

Source: Income and Expenditure Survey (ENIGH 2018)

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 have advantages in 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 3 shows that chains' store openings between 2016 and 2020 present a spatial correlation consistent with the advantages of opening stores in nearby cities.

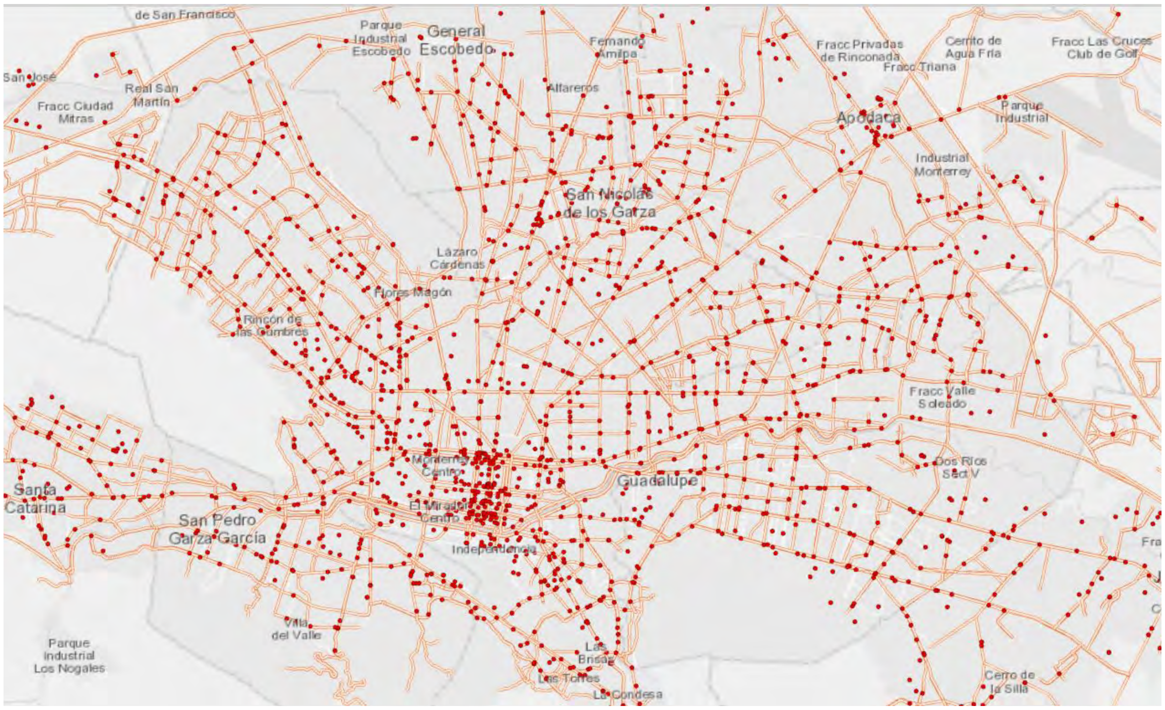
The analysis in Online Appendix B measures the relevance of these advantages in determining the number of stores each chain has in a city. In particular, after controlling with firm-city, year-city, and year-firm fixed effects, 20 additional same-chain stores in nearby cities (cities adjacent to this city and those adjacent to it) are associated with one more store in the city. Stores in nearby cities account for 11% of the total variation in the number of stores each chain has in a city.[20] 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 and bus traffic customers. Chains also place 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 4 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.

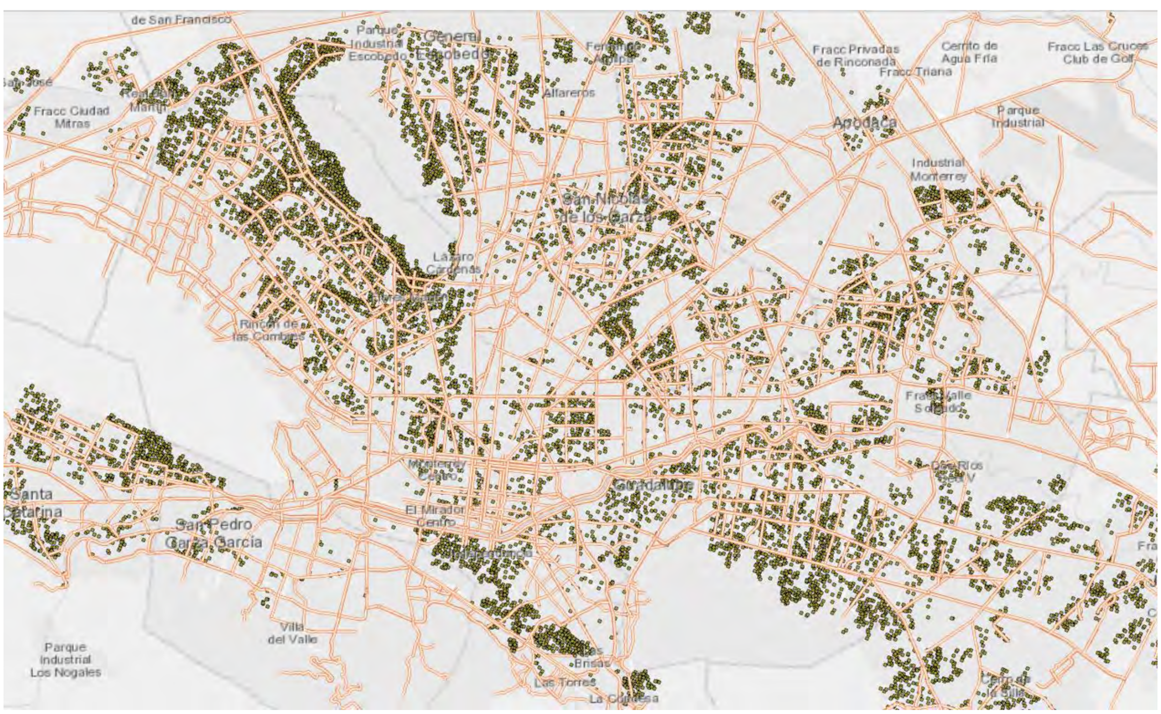
Figure 3: Spatial Correlation in Store Openings by Chain (2016-2020)

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

[20]The 11% 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 4: 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.

V 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 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 exploits two key differences between chains and shops: i) chains have regional economies of scale,[21] 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.[22] Nearby cities are those adjacent to the city and cities adjacent to those (1^{st} and 2^{nd} degree neighbors).[23] 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.

$$Z_{nct} = \underbrace{\left(\sum_{f} (\#StoresNearbyTowns_{fct})^2 \right)^{1/2}}_{\text{Economies of Scale}_{ct}} \times \underbrace{\frac{Total\ wide\ streets\ length_{nc}}{Area_{nc}^{1/2}}}_{\text{Prevalence of Wide Streets}_{nc}} \tag{1}$$

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

[22] 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.

[23] The robustness section presents results using only 1^{st} degree neighbors and also using 3^{rd} degree neighbors. The results are similar and consistent.

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. 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.[24] 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.

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

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

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

where n denotes neighborhood, c denotes city, t denotes census year, and f denotes firm. Equations 2 and 3 include neighborhood fixed effects, ζ_{nc}, and city-year fixed effects, η_{ct}. CS stands for the number of chain stores, and Y_{nct} is the outcome of interest; for example, the number of shops, revenues, profits, neighbors expenditures in shops, prices paid by neighbors, etc. 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.[25]

The exclusion 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 store entering their neighborhood.

A possible concern with the IV 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 is growing the fastest. In particular, the problem would be that the instrument would be correlated with household income, hence with demand

[24] 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.

[25] The robustness section presents results clustering at the neighborhood level, city and year level, city x year level, and city x year and neighborhood level. It also presents results considering the potential correlation of standard errors across adjacent cities and neighborhoods.

faced by shops, violating the exclusion restriction. To address this concern, I present two analyses. First, 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 B 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 a firm-specific.

Second, 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. An alternative placebo check tests whether the instrument correlates with the number of shops in neighborhoods where chains have not yet entered. Column 2 of Table A.1 shows that the instrument does not correlate with the number of shops in neighborhoods where chains have not yet entered.[26]

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.10 shows, the effect on the number of shops stabilizes between a 1 and 1.25 km radius, 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.9 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

[26]For this estimate to imply that the exclusion restriction holds requires assuming that neighborhoods where chains have not yet entered, would have behaved as those where chains entered if chains had not entered. Without this assumption, the no-correlation between the instrument and the number of shops in places where chains do not enter is neither a necessary nor sufficient condition for the exclusion restriction to hold.

the instrument.

There are still concerns that the empirical strategy cannot address. For example, suppose that 7-Eleven has so many stores in a region that it convinces Pepsi to stop selling to shops. Losing Pepsi products would affect shops through a mechanism other than additional chain stores in their neighborhood, violating the exclusion restriction. This example is not a concern because there is no anecdotal evidence of this happening, and the Mexican antitrust authorities ensure this type of practice does not occur.

VI 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 4.6. An expansion from zero to the average number of chain stores in a neighborhood, 6.4, reduces the number of shops by 29 (16%).[27] 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 Column 2, I partially address the issue by introducing neighborhood fixed effects. In Column 3, I further address it by introducing year-city fixed effects. However, the effect in Column 3 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 4, which presents the 2SLS estimates using the instrument. Columns 5 and 6 report the reduced form and first stage estimates.

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 2, and the number of exits decreases by 0.8. These estimates imply that an expansion from zero to the average number of chain stores in a neighborhood reduces entries by 21% and exits by 8%. These results are columns 1 and 2 of Table 3. The reduction in exits might appear surprising at

[27] Conditional on having chain stores, neighborhoods have, on average, 6.4 chain stores and 175 shops.

Table 2: Effect of Chains on Number of Shops

	OLS			2SLS	Reduced Form	First Stage
Dependent Variable:	# of Shops	# of Shops	# of Shops	# of Shops	# of Shops	# of Chain
	(1)	(2)	(3)	(4)	(5)	(6)
Number of Chain Stores	3.27***	-0.57***	-2.01***	-4.47***		
	(0.533)	(0.211)	(0.314)	(0.659)		
Economies of Scale$_{c,t}$ x					-9.73***	2.18***
Chain Suitability$_{m,c}$					(0.855)	(0.254)
Observations	188,630	188,630	188,630	188,630	188,630	188,630
Neighborhood FE		Y	Y	Y	Y	Y
Year x City FE			Y	Y	Y	Y
Clustered SE	City	City	City	City	City	City
Mean Dep. Variable | Chains>0	175	175	175	175	175	6
Mean Chain Stores | Chains>0	6.4	6.4	6.4	6.4	6.4	6.4
KP F-statistic				73.62		

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

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	-2.06***	-0.79***	-0.003***	0.003***
	(0.529)	(0.223)	(0.001)	(0.001)
Observations	156,514	156,514	156,411	156,378
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	86.38	86.38	86.24	86.26

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

first. However, as the model highlights, the effect of chains on the number of shop exits is ambiguous.

On the one hand, it can make some shops unprofitable, increasing the number of exits. On the other hand, if shops' natural exit rate does not change and chains reduce the total number of shops through the decreased entry, the number of shop exits will decrease because there are fewer shops. The estimated reduction in exits implies that the latter effect dominates the former.

Only observing entries and exits for firms that have been alive long enough to appear in a census is a limitation to estimating the effect on shop entry and exit. Two cases arise based on how long the entrant would have survived absent chains. The first case is short entries, where the firm was supposed to enter and exit between censuses. If chains decrease the number of short entries (the same way they reduce the number of regular entries), the effects on entries and exits would be upward biased because short entries are not counted but are expected to be more in the "control" group. The second counterfactual is long entries, where the firm was supposed to enter before the census and exit after the census. If chains decrease the lifespan of these entries so that they also exit before the census, the effects on entries and exits would be downward biased because they are not counted in the "treated" group.

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 can not 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 2 pp (5%) and increases the exit rate by 2 pp (5%). I also estimate the effect on the probability of exit using survival models. Going from zero to the average number of chains in a census tract increases the exit probability of shops between 2.1 and 4.5 pp. Table A.2 reports the estimates of various survival models: Cox, Poisson, and Linear with different combinations of fixed effects and store-level controls.

Consistent with the conceptual framework, Figure 5 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 26%. There are similar effects for resale revenue, value-added, profits per worker, and inventories. These include the effect on shops that remain open and the effects through shops that closed or did not open. The shop level effects are less than 1/3 of the industry impact – the average profits and revenue of shops decline by 7%, 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.

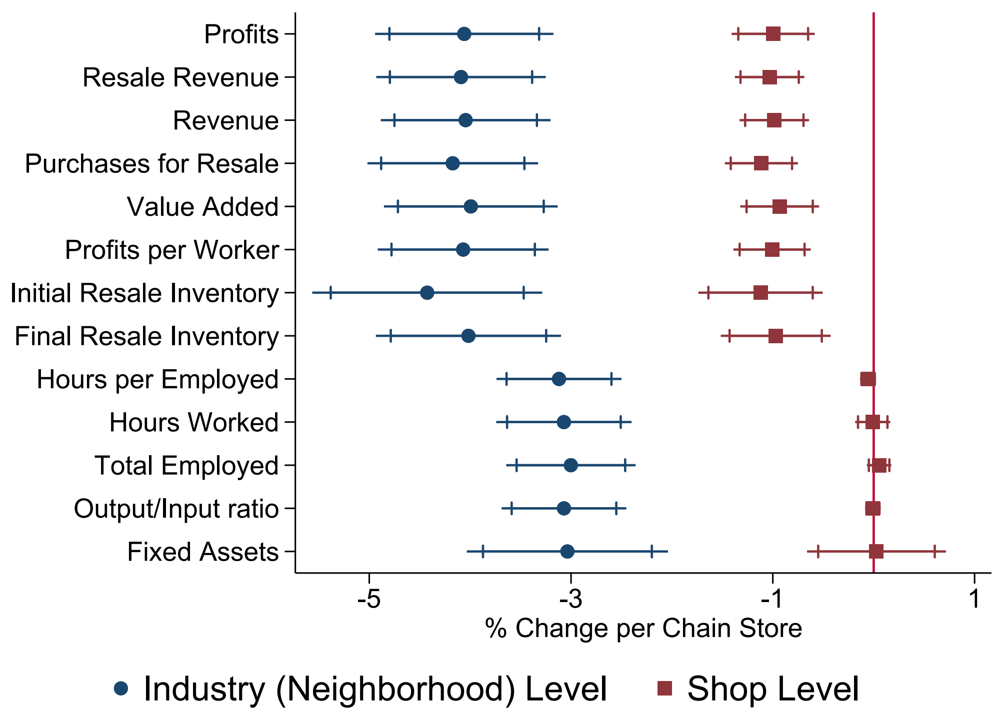


Figure 5: Effects on Shops' Performance

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.

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 4.2%, and equivalently, shops retain 95.8% of their customers. However, the average number of days neighbors visit shops declines by 8%, of which 94% is from customers that continue to visit shops but do so 7% less.[28] The expenditure in shops declines by 13.4%, and 76% of this effect is from customers that continue to purchase in shops but spend less.[29] The 16% reduction in food purchases, shops' top-selling category (90% of sales), accounts for the entire decline in shop purchases.

Figure 6 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, eggs, cigarettes, sweet cookies, and juices, shops retain sales of fresh products like fresh sweet bread, 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 sweet bread, for which sales decline, while sales for fresh sweet bread and fresh bread do not change. Another example is spicy food. On the one hand, neighbors purchase less packed chilies and salsa from shops. 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 16% fewer shops, implying a potential increase in sales of fresh products per shop. This null effect on the revenue of fresh products 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, leading to further 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 share of their food in shops (see Figure 9). The following section discusses comparative advantages that allow shops to survive in more detail.

[28] I obtain the 94% by multiplying the effect conditional on purchasing (-.037) times the share of customers that buy in shops (86%) and divide it by the total effect (-.034).

[29] I multiply the effect conditional on purchasing (-31) times the share of customers that continue to buy in shops (86%) and divide it by the unconditional effect (-35).

Table 4: Effect of Chains on Neighbors' Consumption

Dependent Variable: Consumption in Shops	I[Purchase]	Weekly Visits	Weekly Visits	Purchases ($)	Purchases ($)	Food Purchases ($)	Food Purchases ($)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Number of Chain Stores	-0.004**	-0.034**	-0.037**	-35.39***	-31.38**	-37.99***	-34.16***
	(0.002)	(0.015)	(0.016)	(11.99)	(13.60)	(11.23)	(12.86)
Observations	989,111	989,111	860,016	989,111	860,016	989,111	860,016
Year x City FE	Y	Y	Y	Y	Y	Y	Y
Neighborhood FE	Y	Y	Y	Y	Y	Y	Y
Conditional on Purchase in Week			Y		Y		Y
Mean Dep. Variable | Chains>0	0.86	3.9	4.6	2,559	2,960	2,306	2,675
Avg. Chain Stores | Chains>0	9.68	9.68	9.14	9.68	9.14	9.68	9.14
0 to Avg. # Chain Stores	-4.2%	-8.3%	-7.3%	-13.4%	-9.7%	-15.9%	-11.7%
KP F-Statistic	100.60	100.60	93.16	100.60	93.16	100.60	93.16

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).

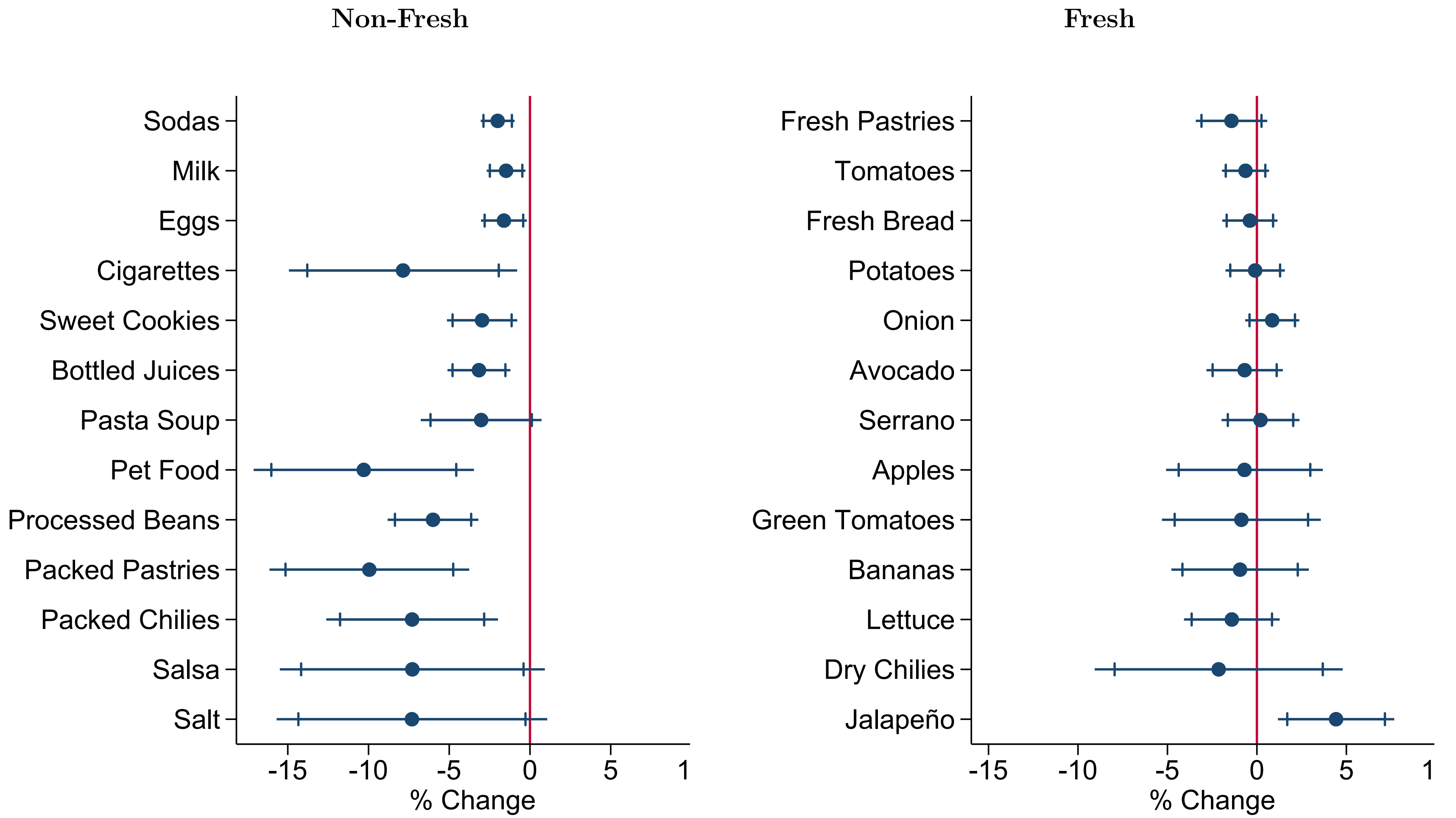


Figure 6: Effect on Neighbors Expenditure in Shops

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; on average, there are nine chain stores in each neighborhood (conditional on at least one chain store). Goods are sorted from top to bottom by their share of shops' revenue. For non-fresh goods, sodas represent 13% of revenue and salt 0.2%. For fresh goods, pastries represent 3% of revenue and jalapeño 0.2%.

VII Discussion

This section provides evidence on why shops survive despite their disadvantages in scale and then discusses consumer welfare implications of the increased competition from chains. First, I show that the adverse effects of chains on shops are smaller for owner-operated and smaller shops. Then, I present results consistent with these smaller and owner-operated shops having comparative advantages in building relationships with their customers, facing lower agency costs, and screening their neighbors to provide them with informal credit to buy in the shop. The second subsection discusses welfare implications by studying the consumption patterns in chains and shops across the household income distribution.

A. Shops' Comparative Advantages

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.[30] However, hybrid stores are different from chains because their owners only have one store. This is the only analysis in the paper that includes hybrid stores.

Figure 7 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 is at the neighborhood, city, time, and shop type level. Hybrid stores are significantly more affected by chains. At the neighborhood level, their drop in profits and value-added are 50% larger than for neighborhood shops. At the store level, the differences are starker. The percentage reductions in profits, hired employees, investment, and inventories are more than double for hybrid stores than for shops.

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, who 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 A.13, I compare the effect of chains on shops that hire employees (7% of all shops)

[30] Figure A.11 displays an example of a hybrid store.

and on owner-operated ones. Even though, on aggregate (neighborhood level), the effect on profits, revenue, and value-added are not statistically different for owner-operated and shops that hire employees, there significant differences in the effects at the shop level. Shops that hire employees suffer at least 70% larger percentage declines relative to owner-operated shops in profits, value-added, revenue, profits per worker, and inventories.

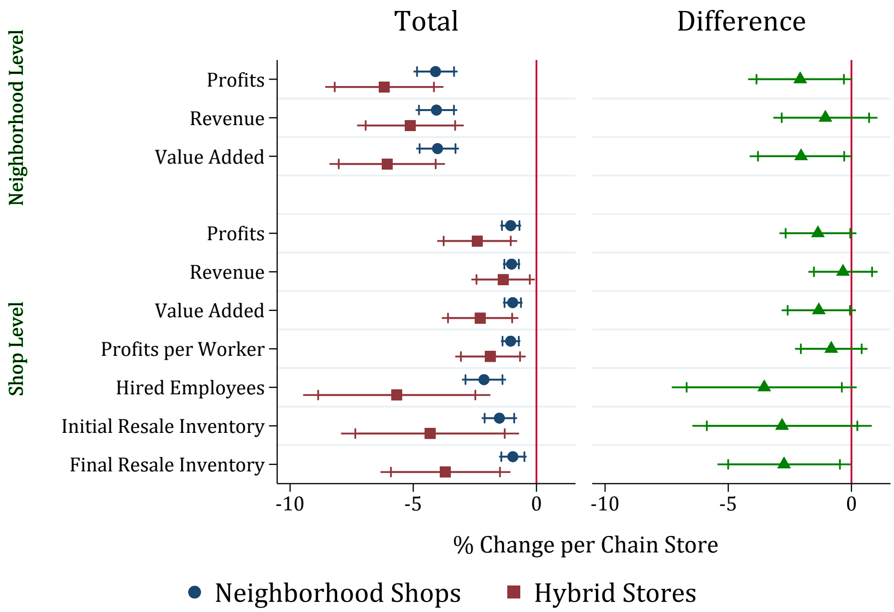


Figure 7: Effects of Chains on Shops' Performance by Shop Size

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.

Owner-operated shops have lower agency costs because 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 6 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.

Relationships between shops and neighbors are likely stronger if the owner is also a neighbor. Even though information on where the owner lives is unavailable, I use whether

Figure 8: 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 ninety-five percent confidence intervals plotted.

the shop pays rent or not as a proxy of whether the shop is next to the owner's house. Shops in the owners' houses are likely to have stronger relationships with the neighborhood because the owner is also a neighbor. Figure 8 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 12% larger in revenue. At the shop level, the percentage reduction for hybrid stores is 72% larger in profits, 75% larger in revenue, and 68% larger in profits per worker.

Relationships between the shops and the neighbors are hard to measure, but they likely grow with time. Data on how long a customer has lived in a neighborhood is unavailable. However, suppose I assume that homeowners have lived, on average, longer in the neighborhood or are more involved with the community. In that case, I can use home ownership as a proxy for the strength of the relationship with shops. Consistent with the importance of relationships between shops and customers, I find that controlling for socioeconomic strata, home type, income, and age of the household head, homeowners purchase 13% less in chains and 9% more in shops (see Table A.8).

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.12 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 four 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.

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 give 69% of the credit used by families in the first income quintile to purchase food and drinks.[31] With an expansion from 0 to the average number of chain stores in the neighborhood, the amount of credit supplied by shops doubles (in monetary terms and number of goods, see Table A.3). This expansion in purchases in shops using informal credit is despite the reduction in the number of shops. These statistics and results highlight that in a context with limited access to credit and liquidity constraints, shops' relationships with their neighbors solve, even if just partially, the credit market frictions that consumers face and give shops a significant comparative advantage.

Distance is potentially critical in determining whether the household purchases in a shop or a chain. Households may choose whatever store is closest to them, and because there are more shops than chains, it is more likely that the nearest establishment is a shop. Unfortunately, I do not know how far the shops and chain stores are from households. To circumvent this lack of data, I use the size of the neighborhood, which varies due to differences in census tract sizes, as a proxy of how far chain stores are from the consumers and shops. The idea is that the additional chain store opening in smaller neighborhoods will, on average, be closer to incumbent shops and households. If the distance to the store is important, the negative effect of chains on shops in smaller neighborhoods should be more prominent.

However, smaller neighborhoods might have fewer shops and fewer chains stores, implying that: i) the effect on the number of shops might be smaller because there are fewer shops, and ii) the effect on the number of shops might be larger because there are fewer chain stores

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

(if the marginal effect of a chain store is decreasing in the number of chain stores). To take this into account, Figure A.15 reports the effect of an increase of 1% in the number of chains stores (relative to the average) on the number of shops relative to the average number of shops, where both averages are those corresponding to the neighborhood size decile. The results display a lack of evidence on the distance to the establishment being critical in the effect of chains on the number of shops.

The evidence in this section suggests that not only do shops survive, but they also have incentives not to grow. On the one hand, when shops grow, hire employees, move out of the owner's house, and target customers outside the neighborhood, they can potentially increase their revenue and profits and exploit the advantages of operating at a larger scale. However, this growth will come at the expense of losing comparative advantages that stem from being small and owner-operated, making them less differentiated and more vulnerable to competition from chains.

B. Consumer Welfare Implications

The entry of chains can have both a positive and negative impact on consumer welfare. Welfare increases for consumers who prefer to purchase in chains or goods offered by chains because chains are now more available. However, the expansion of chains reduces the number of shops, potentially reducing access to shops for consumers who prefer purchasing in shops. I focus on these mechanisms because chains do not have a statistically significant effect on shops' prices (see Figure A.14). Figure 9 presents on the left the share of expenses in food and beverages in chains and shops by households' income decile and on the right the purchase frequency. Lower-income families spend a larger share of their income in shops and almost nothing in chains; they also visit shops more than twice as often as the highest income decile households. The highest-income families are the ones that purchase in chains the most and most frequently. Hence, these households are the ones who may benefit the most from the expansion of chains.

The key to determining whether the gains for higher-income households come at the expense of lower-income families is whether low-income households lose access to shops. Figure 6 shows that purchases of fresh products in shops do not decline, despite a reduction in the number of shops by 16%, suggesting that households do not lose access to shops. However, even if shops are still available for these households, these families might still be worse off because these shops are now, on average, further away (there are fewer shops), and it is now more costly to get there. The increase in travel costs is likely small because there is, on average, one shop every three blocks even by the end of the studied period.

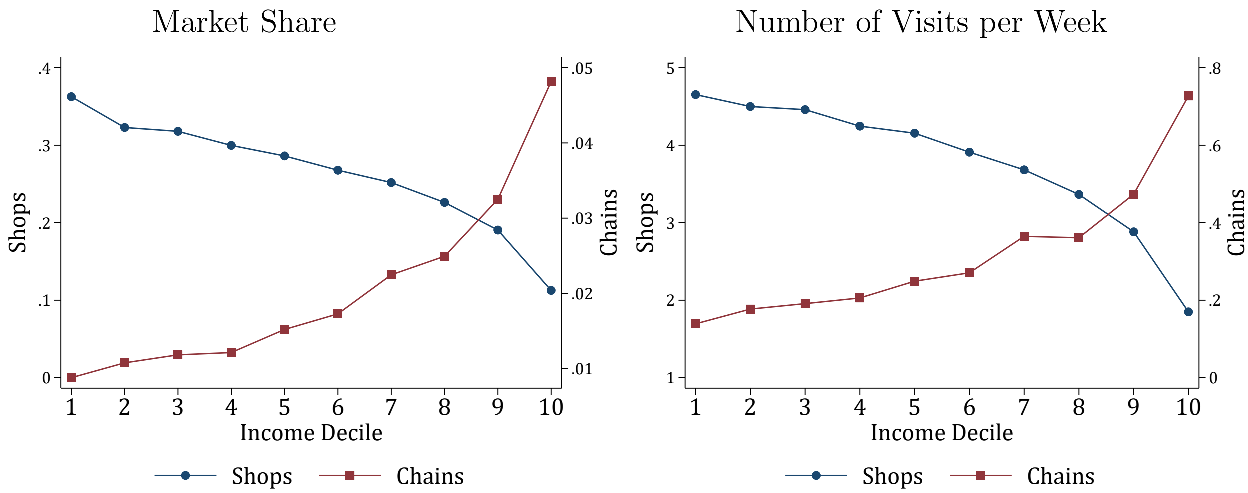


Figure 9: Market Shares and Number of Visits by Income Deciles

Source: Income and Expenditure Survey (ENIGH 2018). Food expenses in restaurants are not included.

VIII Robustness

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

Table 5 present 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 testing the monotonicity assumption is less transparent with multiple instruments, and the second is that the first stage of the IV is weaker. 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 almost identical 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 that lead to a very 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

Table 5: Robustness - Alternative IV Specifications

	Dependent Variable: # of Neighborhood Shops										
	Main	Per Chain	Squared & Cubed	1st Neighbors	3rd Neighbors	Squared Sum	Sum	Lasso1	Lasso2	Conv 1999	Chain $\text{Stores}_{t\text{-}1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Number of Chain Stores	-4.47***	-4.15***	-4.57***	-4.25***	-4.49***	-4.78***	-4.43***	-3.93***	-3.92***	-4.07***	-4.94***
	(0.659)	(0.503)	(0.657)	(0.713)	(0.596)	(0.836)	(0.669)	(0.513)	(0.540)	(0.565)	(0.678)
Observations	188,630	188,630	188,630	188,630	188,630	188,630	188,630	188,630	188,630	188,630	159,289
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	6.4	6.4	6.4	6.4	6.4	6.4	6.4	6.4	6.4	6.4	6.7
From 0 to Avg. # Conv. Stores	-16.5%	-15.3%	-16.8%	-15.6%	-16.5%	-17.6%	-16.3%	-14.5%	-14.4%	-15.0%	-18.9%
KP F-statistic	73.62	31.13	36.19	79.16	109.11	44.71	65.03	64.49	56.40	79.61	104.27

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. Columns 8 and 9 create a measure of suitability lasso to select the relevant variables to predict the number of chain stores. 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 lagged number of chain stores in nearby cities to construct the instrument.

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. The lasso estimations also include the square, cube, and natural logarithm transformation of each variable totaling more than 2,600 variables in each analysis. The lasso in column 8 selected 675 variables, and the one in column 9 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.[32] The difference between Columns 8 and 9 is that column 9 does not include variables from the 2000 population census. 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 are also suitable for chains in the following two decades. These three alternative measures of suitability render estimates similar and within one standard error of the estimate in the main specification.

To capture that chains exploit economies of scale by opening stores in nearby cities, throughout the paper, I use the contemporary number of convenience chain stores in nearby cities: the spatial correlation in chains' expansion. I could also measure regional economies of scale using serial correlation instead: chains are more likely to expand in areas where they already have a presence. Column 11 uses the lagged number of chain stores in nearby cities to construct the instrument instead of the contemporary number. The estimate is larger than in the main specification but within one standard error. This is not the preferred specification because it reduces the sample size by not including observations from 1999.

Table 6 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. The estimate is similar and consistent with that of the main specification. The economic censuses include the number of establishments for 154 business types other than shops and chains (e.g., restaurants, supermarkets, butchers, hospitals, liquor stores, shoe stores, pet stores, hardware stores, car dealers, banks, schools, and universities). To

[32]This could mean that variation in the variable, or of another variable it is correlated to, has a significant impact on the number of chain stores in the census tract.

Table 6: Robustness - Adding Controls

	Dependent Variable: # of Neighborhood Shops									
	Main	Nearby Chains Control	Control Other Businesses PCA	Control Other Businesses FA	Pop. Census Controls	Large Cities Avg. pop 880K	HH Sample	HH Controls	HH Controls PCA	HH Controls FA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Number of Chain Stores	-4.47***	-4.70***	-4.64***	-3.97***	-3.37***	-5.94***	-5.39***	-5.52***	-5.41***	-5.41***
	(0.659)	(0.986)	(0.951)	(0.914)	(0.708)	(1.579)	(0.877)	(0.879)	(0.870)	(0.871)
Observations	188,630	188,630	187,942	187,942	182,082	36,063	49,481	49,481	49,481	49,481
Neighborhood FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year x City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Mean Dep. Variable | Chains>0	175	175	175	175	179	200	212	212	212	212
Mean Chain Stores | Chains>0	6.4	6.4	6.4	6.4	6.5	8.1	9.4	9.4	9.4	9.4
From 0 to Avg. # Conv. Stores	-16.5%	-17.3%	-17.1%	-14.6%	-12.3%	-24.1%	-23.9%	-24.5%	-24.0%	-24.0%
KP F-statistic	73.62	56.72	83.20	78.03	64.15	14.17	97.53	95.26	98.71	97.67

Note: The table displays the estimation of Equation 3 using 2SLS with alternative controls. Column 2 uses the principal components with an eigenvalue larger than one from a PCA to control for the presence of other businesses in the neighborhood (e.g., restaurants, supermarkets, butchers, hospitals, liquor stores, shoe stores, pet stores, hardware stores, car dealers, banks, schools, and universities). Column 3 uses the factors with an eigenvalue larger than one from a factor analysis as controls for the presence of other businesses in the neighborhood. Column 4 controls for the number of convenience chain stores around the neighborhood. The measure of chain stores around the neighborhood is the number of chain stores the neighborhood would have if neighborhoods were constructed using a 2km radius circle instead of a 1km minus those in the 1km radius. Column 5 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. I use linear interpolation and extrapolation to match the controls to the economic census years. Column 6 presents the results of the main specification but restricts the sample too large cities with an average population of 800,000. Column 7 restricts the sample to neighborhoods for which there is consumption data. Column 8 includes the following household controls: 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. Columns 9 and 10 use principal components and factor analyses to control for the same household variables keeping the components or factors with an eigenvalue larger than one.

control for the presence of these businesses, I use a principal components analysis and keep the components with an eigenvalue larger than one as controls in Column 3. Alternatively, Column 4 uses a factor analysis instead and keeps all the factors with an eigenvalue larger than one as controls. The results of columns 3 and 4 are consistent with those of the main specification. Column 5 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. I use linear interpolation and extrapolation to match the controls to the economic census years. The estimate is smaller but consistent with that of the main specification.

Columns 8 to 10 add household controls from the consumption data (ENIGH) to the main specification, and the results are robust to include these or not. The consumption data, on average, will have households from larger cities with neighborhoods with more shops and chains. Column 6 presents the results of the main specification but restricts the sample to large cities with an average population of 880,000, and the estimate of interest is similar in magnitude to the one in column 7, which restricts the sample to neighborhoods for which there is consumption data. Column 8 includes the following household controls: 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. Columns 9 and 10 use principal components and factor analyses to control for the same household variables keeping the components or factors with an eigenvalue larger than one.

Table A.4 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 3.6%, it is 15.2% for those with an average population of 260,000, and 24.1% for those with an average population of 880,000 thousand.

Table A.5 presents the results of the estimation of Equation 3 but uses the natural logarithm of the number of shops and chains. Column 4 uses the natural logarithm of the number of shops as the dependent variable. 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.

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.10 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 effect of each additional chain store in the neighborhood on the number of shops ranges from a reduction in shops by 2 to 4.8. The negative effect stabilizes at 1 - 1.25 km, consistent with these neighborhood sizes capturing all of the effects of the additional chain store. Table A.6 replicates Table 2, but defining the neighborhoods as census tracts. This is the smallest possible neighborhood size. The patterns in the estimates are consistent. The OLS estimates underestimate the negative effect of chains, fixed effects partially reduce the bias, and the IV addresses the bias due to unobservable neighborhood-specific shocks affecting both chain stores and shops.

I cluster standard errors at the city level throughout the paper. Table A.7 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 can not estimate standard errors that take into account these potential correlations in my full sample. Hence, I run 500 iterations with 5,000 randomly selected neighborhoods. I compute the standard errors at the city level and correct for the potential correlation of unobserved shocks across adjacent cities and 2^{nd}-degree adjacent cities.[33] The graph on top of Figure A.16 shows that clustering at the city level, as done throughout the paper, is the most conservative alternative. In only four out of the five-hundred iterations, the widest confidence interval is not the one clustering at the city level. I repeat an equivalent analysis to take into account the potential correlation in errors across adjacent neighborhoods. The results, displayed at the bottom of Figure A.16, show that clustering at the city level is more conservative in each of the five hundred iterations. 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.

IX 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

[33]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*.

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. Consistent with a model of differentiated competition between chains and shops, 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 relationships with their customers, and offering informal credit. Shops not only survive, but they have incentives not to grow. If shops grow, hire employees, and increase their catchment area, they may lose the distinct comparative advantages of being small and owner-operated, allowing them to differentiate and survive competition from chains.

In this context, the standard prediction of a more efficient entrant leading to the reallocation of resources through the exit of less efficient firms does not occur. In particular, the small and less efficient type of firm delivers the most value-added to customers in Mexico by easing cash and credit constraints. These small shops, though less efficient, have comparative advantages in offering ripe products, which cash-constrained customers consume the same day. Moreover, their relationships with their customers allow them to offer informal credit to consumers without formal access. The combination of demand factors such as credit and cash constraints and the comparative advantages of shops on easing them allow shops to compensate for their disadvantages in scale.

While the estimates are specific to the context of this paper, 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

Tables

Table A.1: Relationship Between Instrument and Number of Shops

	Dependent Variable: Number of Shops	
	Base	No Chain Stores in Neighborhood
	(1)	(2)
Economies of Scale$_{c,t}$ x Chain Suitability$_{m,c}$	-9.73***	3.46
	(0.855)	(3.416)
Observations	188,630	79,868
Clustered SE	City	City
Market & Year-City FE	Y	Y

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:		Dependent Variable: Store Level (Exit=1)							
	Cox		Poisson				OLS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Number of Chain Stores	0.047***	0.039***	0.047***	0.039***	0.030***	0.030***	0.021***	0.017***	0.013***	0.014***
	(0.0012)	(0.0012)	(0.0008)	(0.0008)	(0.0009)	(0.0019)	(0.0004)	(0.0004)	(0.0005)	(0.0009)
Observations	1,892,525	1,643,883	1,892,525	1,643,883	1,643,612	1,641,019	1,892,525	1,643,883	1,643,873	1,643,184
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. Column 1 and 2 are Cox survival models. Column 3-5 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 underlining assumptions of each method. Columns 6-8 are OLS estimates with age of establishment fixed effects.

Table A.3: Effect on Neighbors' Purchases using Informal Credit

	Dependent Variable:			
	# Goods Purchased in Shops using Credit		Purchases in Shops using Credit $	
	(1)	(2)	(3)	(4)
Number of Chain Stores	0.006*	0.007*	2.357*	2.538
	(0.064)	(0.092)	(0.093)	(0.131)
Mean Dependent Variable	0.064	0.073	21.96	25.02
Observations	988,030	866,969	988,030	866,969
Mean Conv Chain Stores | Chains>0	9.7	9.1	9.7	9.1
Effect from 0 to Avg. # Chain Stores	95.4%	84.2%	103.9%	92.6%
KP F-statistic	100.55	93.88	100.55	93.88
Conditional on Purchasing in Shops		Y		Y

Note: The table displays the estimation of Equation 3 using 2SLS where the dependent variable is the number of goods purchased using store credit and the amount in pesos of purchases using credit. Household controls include household total expenditure, total expenditure in neighborhood shops, income per capita, and age of household head.

Table A.4: 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	-4.47***	-1.39**	-3.96***	-5.94***
	(0.659)	(0.648)	(0.605)	(1.579)
Observations	188,630	89,128	65,165	36,063
# of Cities	1,961	1,813	120	29
Neighborhood & Year x City FE	Y	Y	Y	Y
Mean Dep. Variable | Chains>0	175	124	192	200
Mean Chain Stores | Chains>0	6.4	3.2	7.4	8.1
Effect from 0 to Avg. # Conv. Stores	-16.5%	-3.6%	-15.2%	-24.1%
KP F-statistic	73.62	109.94	115.41	14.17

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

Table A.5: Robustness - Logarithmic Specifications

	Dependent Variable: # of Neighborhood Shops					
	OLS	OLS	OLS	2SLS	2SLS (Log-Linear)	2SLS (Log-Log)
	(1)	(2)	(3)	(4)	(5)	(6)
Number of Chain Stores	3.27***	-0.57***	-2.01***	-4.47***	-0.03***	-0.70***
	(0.533)	(0.211)	(0.314)	(0.659)	(0.003)	(0.107)
Observations	188,630	188,630	188,630	188,630	188,630	188,630
Neighborhood FE		Y	Y	Y	Y	Y
Year x City FE			Y	Y	Y	Y
Mean Dep. Variable | Chains>0	175	175	175	175	175	175
Mean Chain Stores | Chains>0	6.4	6.4	6.4	6.4	6.4	6.4
From 0 to Avg. # Conv. Stores	12.0%	-2.1%	-7.4%	-16.5%	-18.9%	
KP F-statistic				73.62	73.62	34.54

Note: The table displays the estimation of Equation 3. Column 4 uses the natural logarithm of number of shops as the dependent variable. Column 5 uses the natural logarithm of number of shops as the dependent variable and the natural logarithm of number of chains stores as dependent variable.

Table A.6: Robustness - Census Tract Level Effect

	OLS			2SLS	Reduced Form	First Stage
Dependent Variable:	# of Shops	# of Shops	# of Shops	# of Shops	# of Shops	# of Chain
	(1)	(2)	(3)	(4)	(5)	(6)
Number of Chain Stores	0.02	-0.29***	-0.58***	-2.06***		
	(0.195)	(0.074)	(0.059)	(0.327)		
Economies of Scale$_{c,t}$ x					-0.27***	0.13***
Chain Suitability$_{m,c}$					(0.038)	(0.013)
Observations	190,499	190,499	190,499	190,499	190,499	190,499
Neighborhood FE		Y	Y	Y	Y	Y
Year x City FE			Y	Y	Y	Y
Clustered SE	City	City	City	City	City	City
Mean Dep. Variable | Chains>0	13	13	13	13	13	2
KP F-statistic				93.62		

Note: The table replicates Table 2, but defining the neighborhoods as census tracts. This is the smallest possible neighborhood size.

Table A.7: Robustness - Alternative Standard Errors

	Dependent Variable: # of Neighborhood Shops				
	(1)	(2)	(3)	(4)	(5)
Number of Chain Stores	-4.47***	-4.47***	-4.47***	-4.47***	-4.47***
	(0.659)	(0.280)	(0.641)	(0.448)	(0.410)
Observations	188,630	188,630	188,630	188,630	188,630
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
Mean Dep. Variable | Chains>0	175	175	175	175	175
Mean Chain Stores | Chains>0	6.4	6.4	6.4	6.4	6.4
From 0 to Avg. # Conv. Stores	-16.5%	-16.5%	-16.5%	-16.5%	-16.5%
Underid. KP LM stat	30.50	3.20	2.99	93.47	88.77
Weak ID F statistic	36,202	36,202	36,202	27,934	36,202
KP F-statistic	73.62	129.48	54.69	160.15	194.96

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

Table A.8: Purchases in Chains and Shops by Home-Ownership

	Dependent Variable: $ Purchases in Store											
	Convenience Chains						Corner Shops					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
I[Owns Living Space=1]	-75.4***	-54.3***	-54.2***	-44.2***	-66.2***	-26.9*	137.4***	90.3***	90.2***	11.9	167.7***	196.1***
	(17.9)	(14.2)	(14.2)	(13.8)	(14.2)	(14.3)	(40.8)	(34.7)	(34.5)	(32.8)	(32.2)	(29.9)
Mean Dependent Variable	193	193	193	193	193	193	2,128	2,128	2,128	2,128	2,128	2,128
Observations	36,016	35,966	35,966	35,966	35,966	35,966	36,016	35,966	35,966	35,966	35,966	35,966
Cluster SE	City	City	City	City	City	City	City	City	City	City	City	City
Census Tract FE		Y	Y	Y	Y	Y		Y	Y	Y	Y	Y
HH Socioeconomic Strata FE			Y			Y			Y			Y
HH Dwelling Type FE				Y		Y				Y		Y
HH Income pc decile FE					Y	Y					Y	Y
HH Head Age Contol						Y						Y

Note: The table displays the estimates of regressing the expenditure at the household level in shops/chains on a dummy variable of whether the household owns its home using data from ENIGH 2018.

Figures

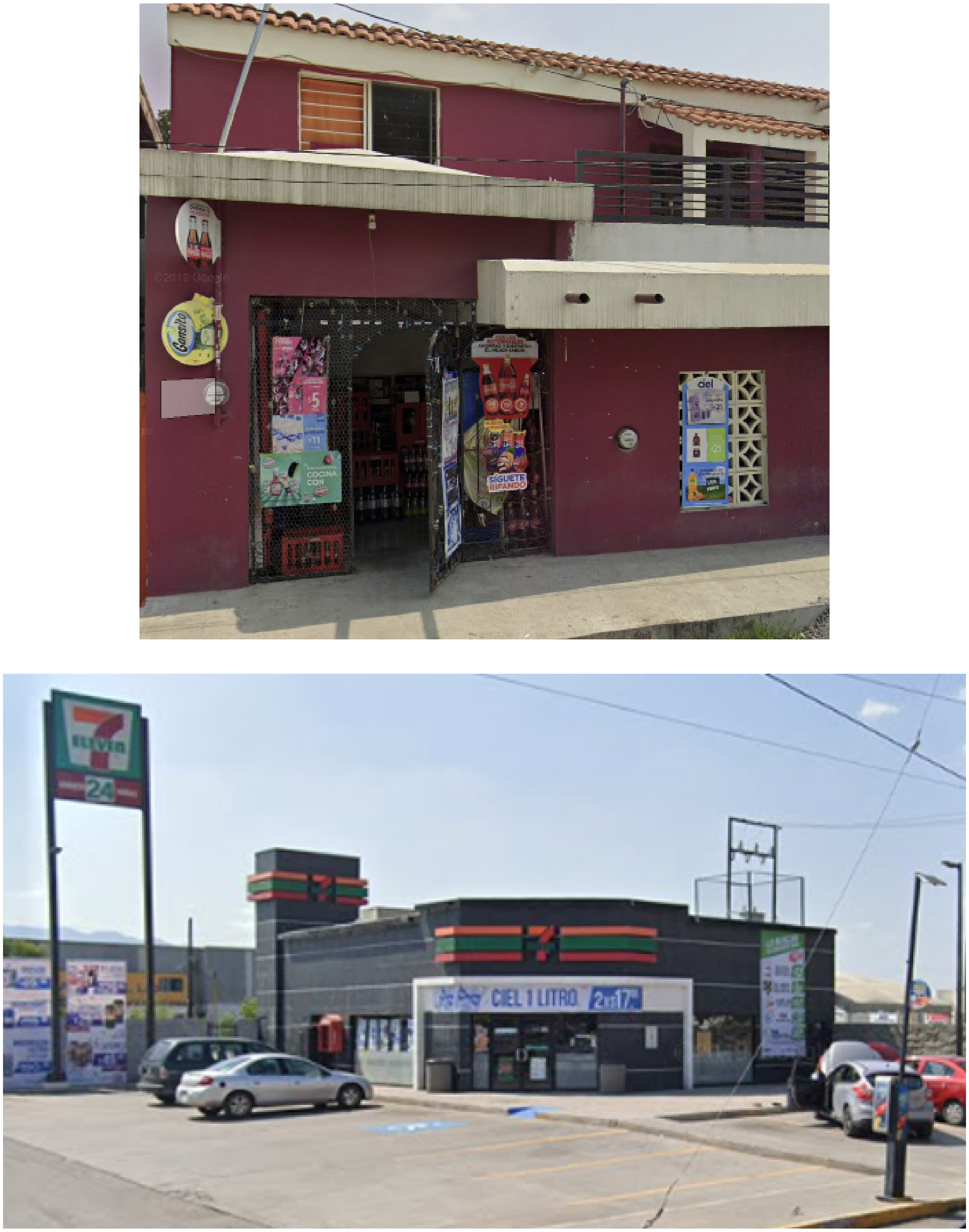


Figure A.1: Shops and Chains

Source: Google Maps
Note: The figure contains an example of a shop (left) and a chain store (right) in Saltillo, Mexico.

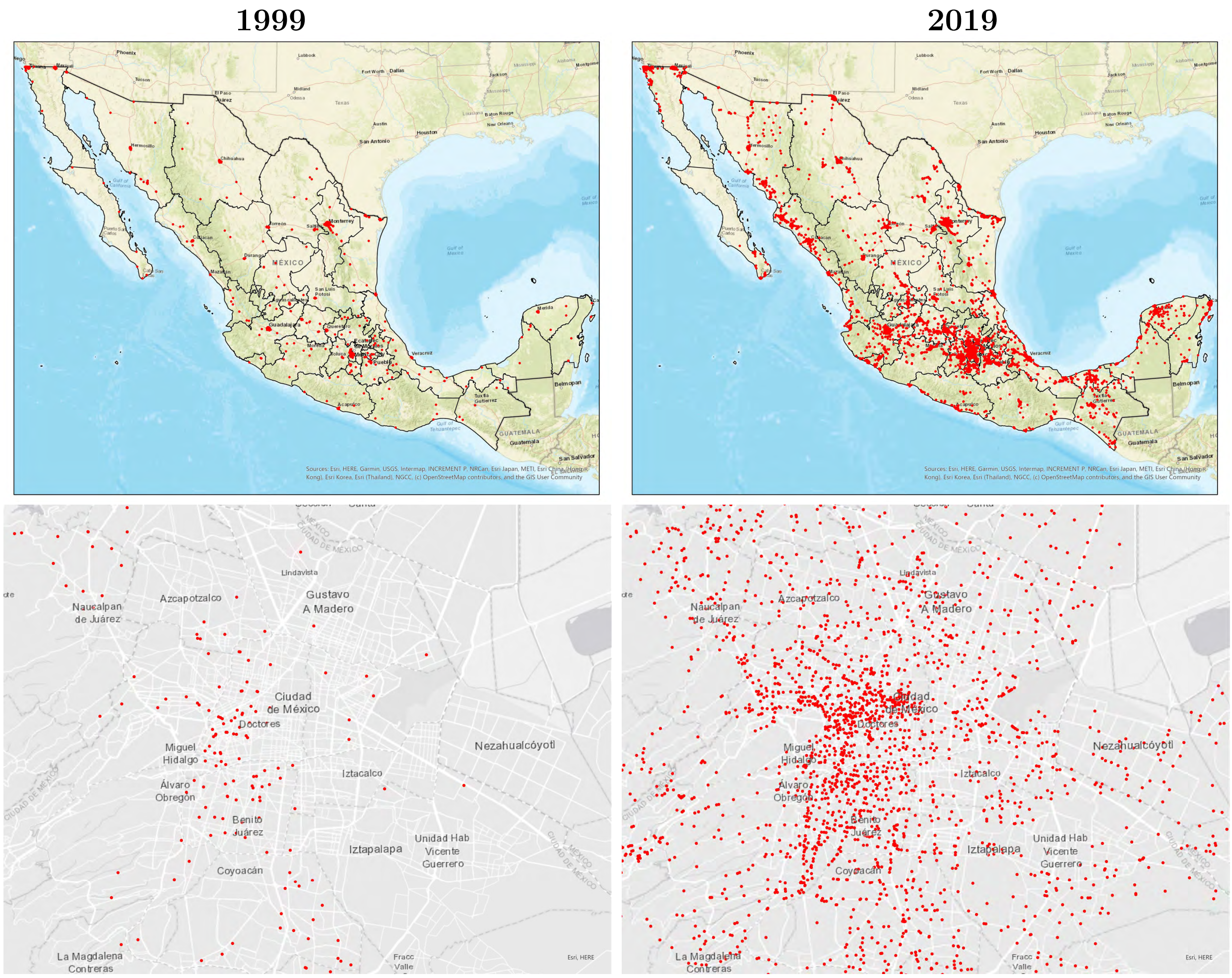
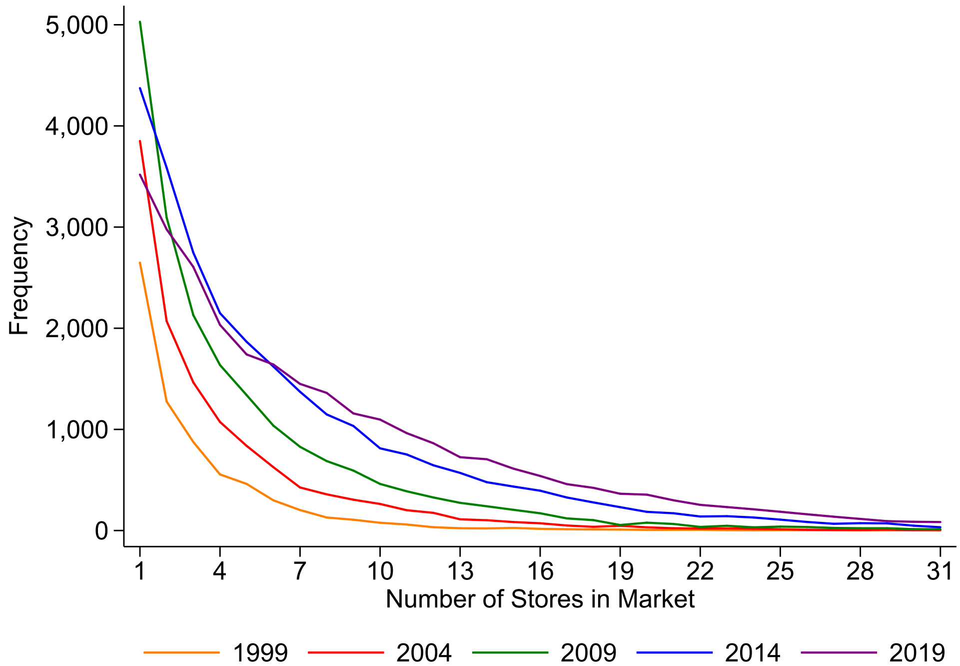


Figure A.2: Chain Stores Expansion

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) Distribution of Neighborhoods by Number of Chain Stores



B) Distribution of Neighborhoods by Number of Shops

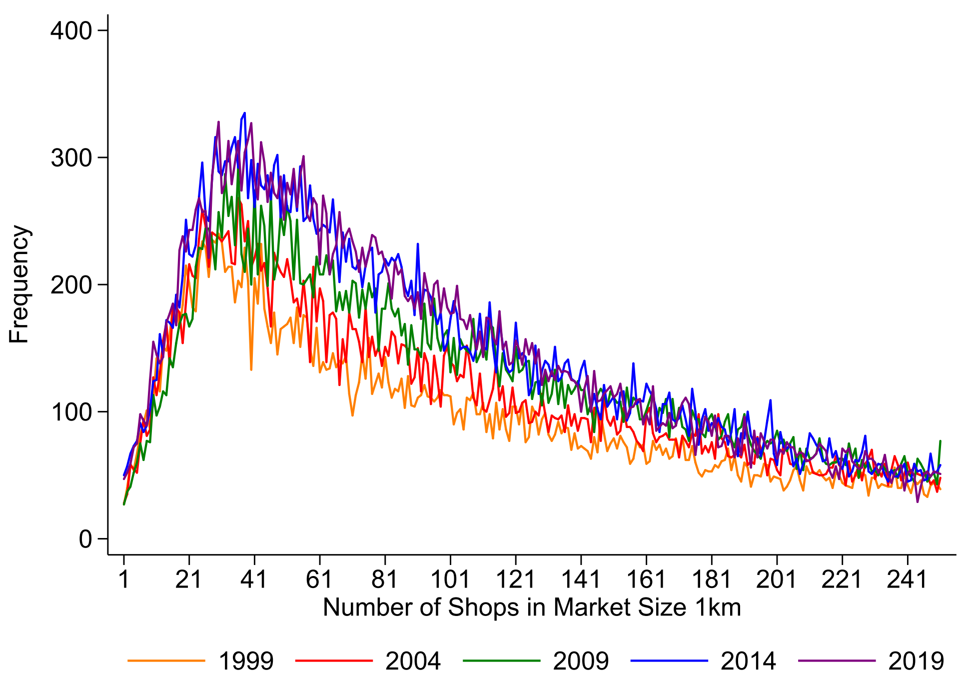


Figure A.3: Frequency Distribution by Number of Shops and Chain Stores

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.

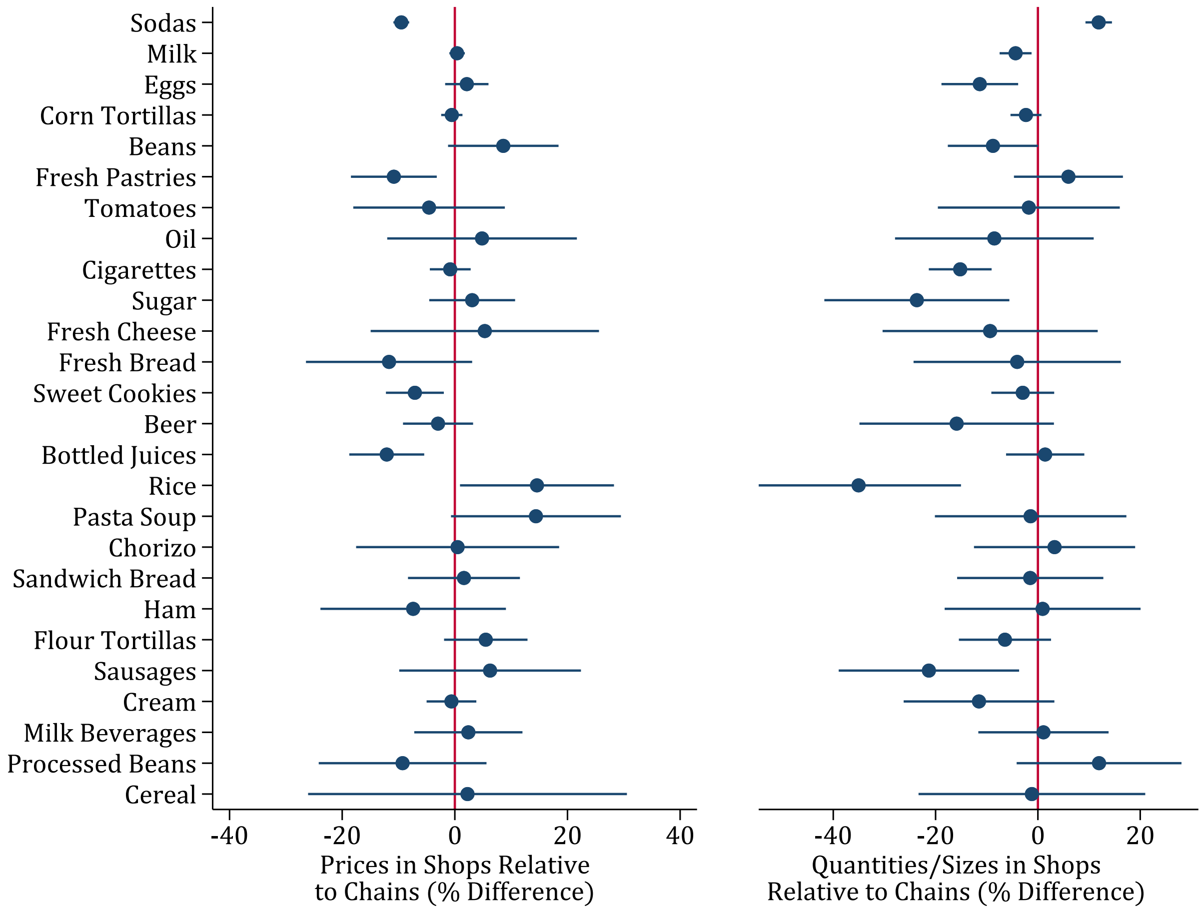


Figure A.4: Prices and Quantities/Sizes Differences Between Chains and Shops

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 is priced per kilogram.

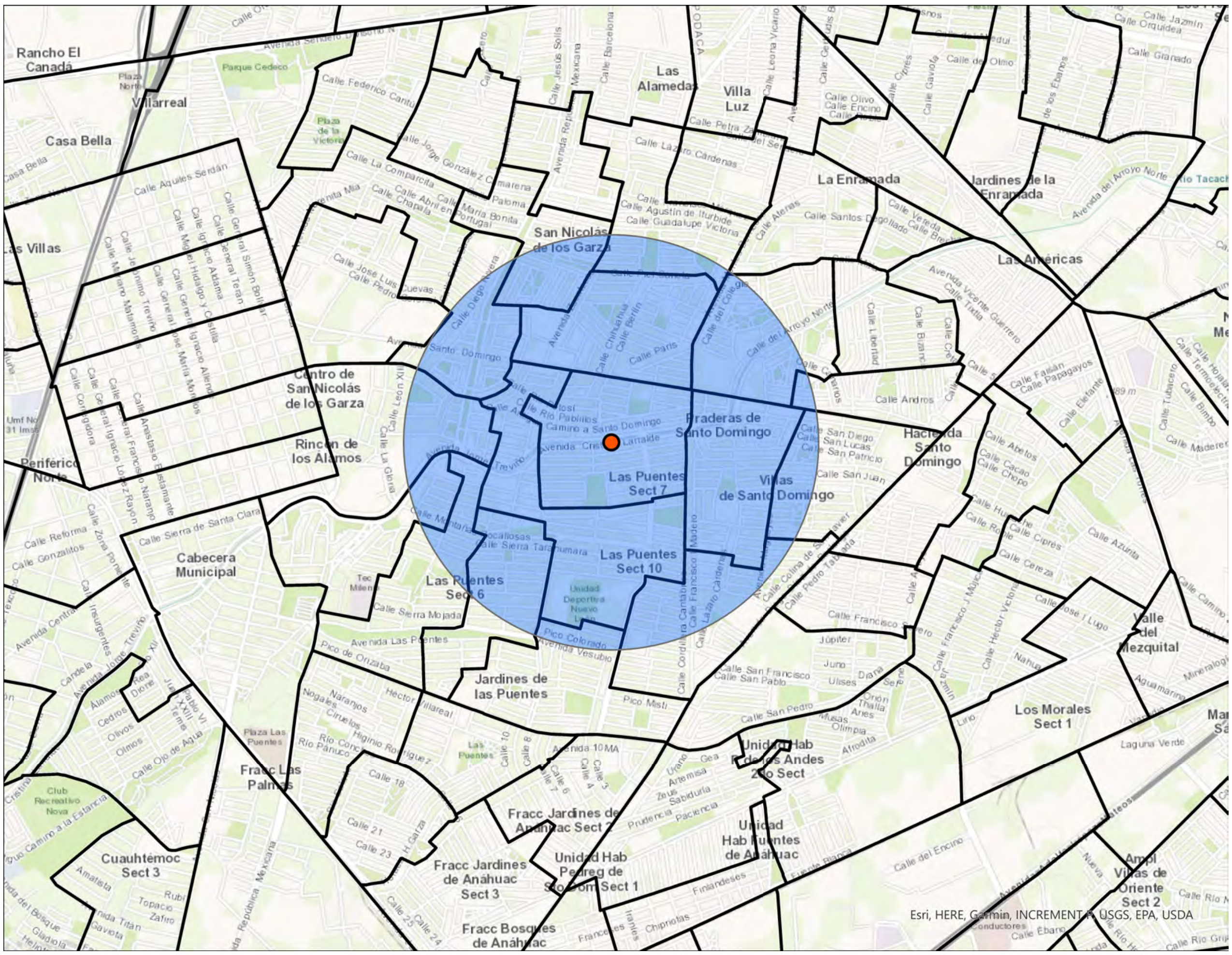


Figure A.5: Market Definition

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.

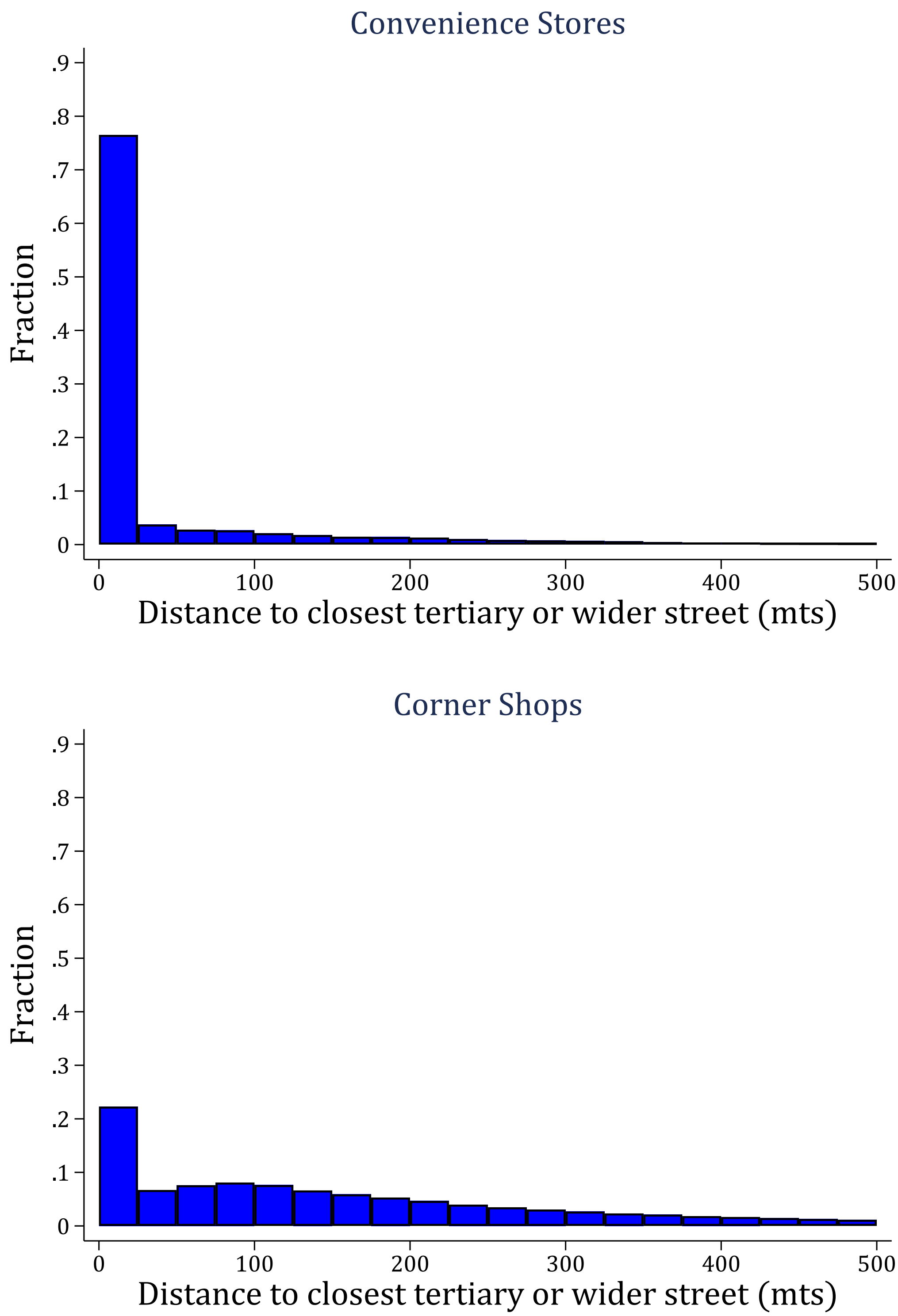


Figure A.6: Distance to Closest Wide Street

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.

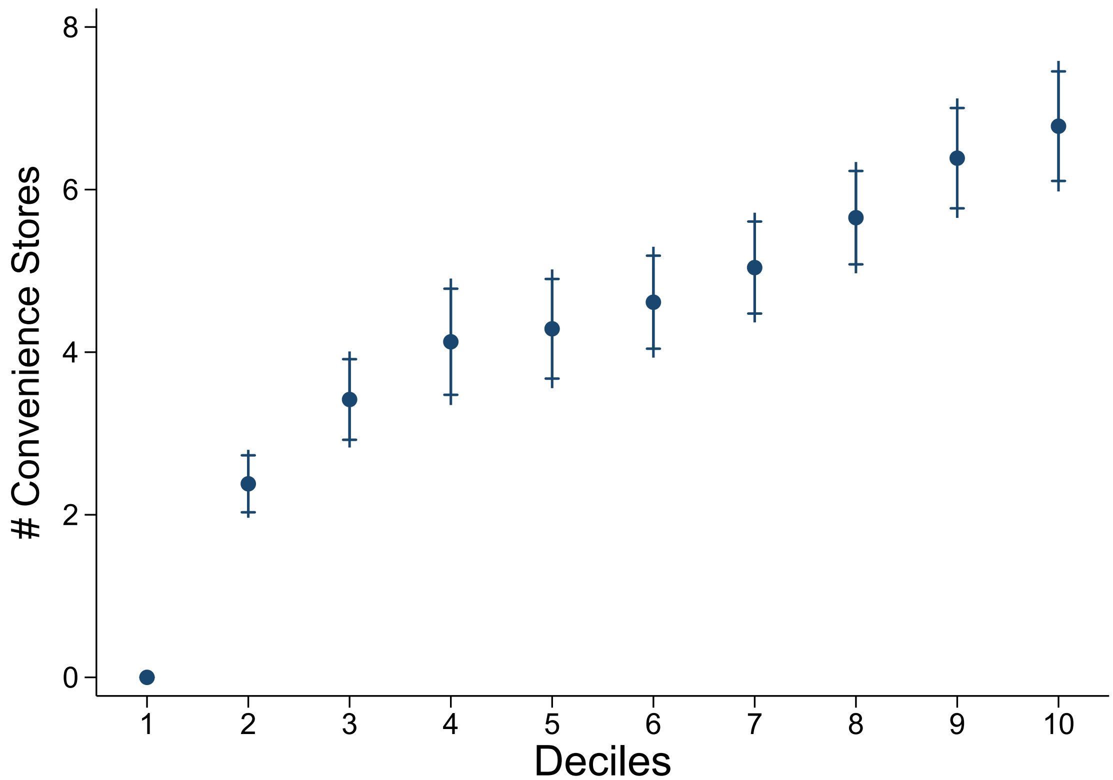


Figure A.7: Relationship Between the Instrument and the Number of Chain Stores

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.

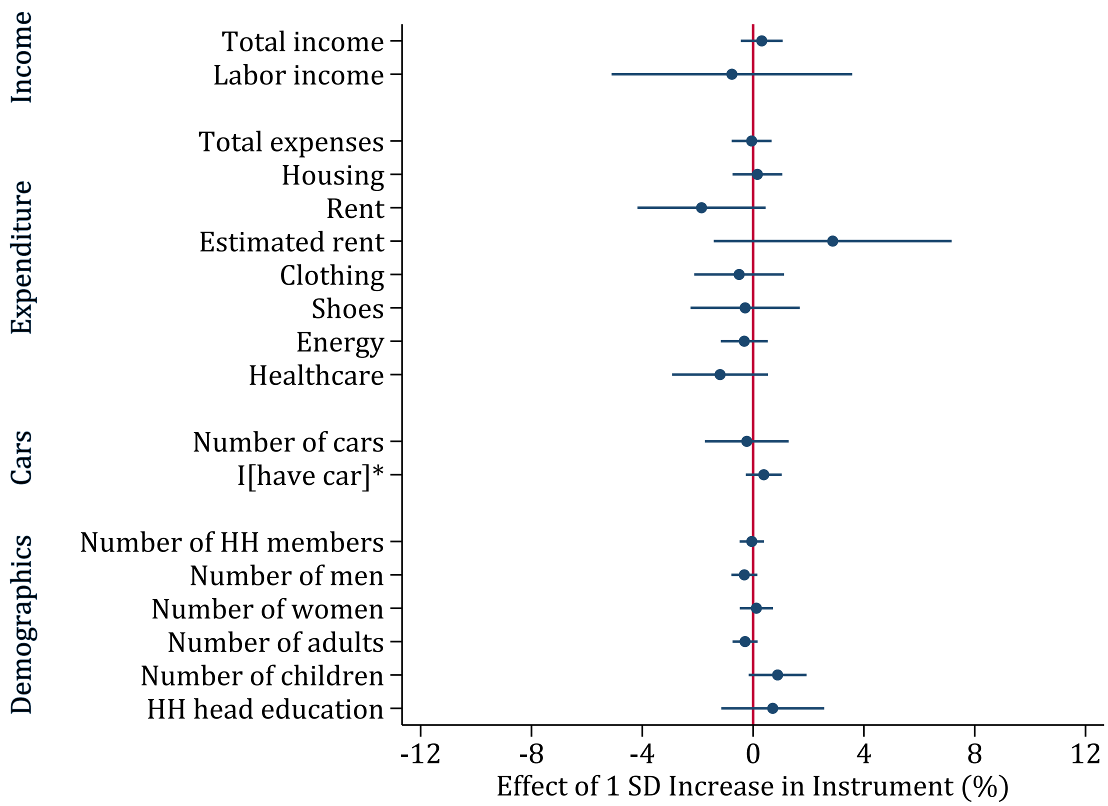


Figure A.8: Placebo - Relationship Between the Instrument and Household Characteristics

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

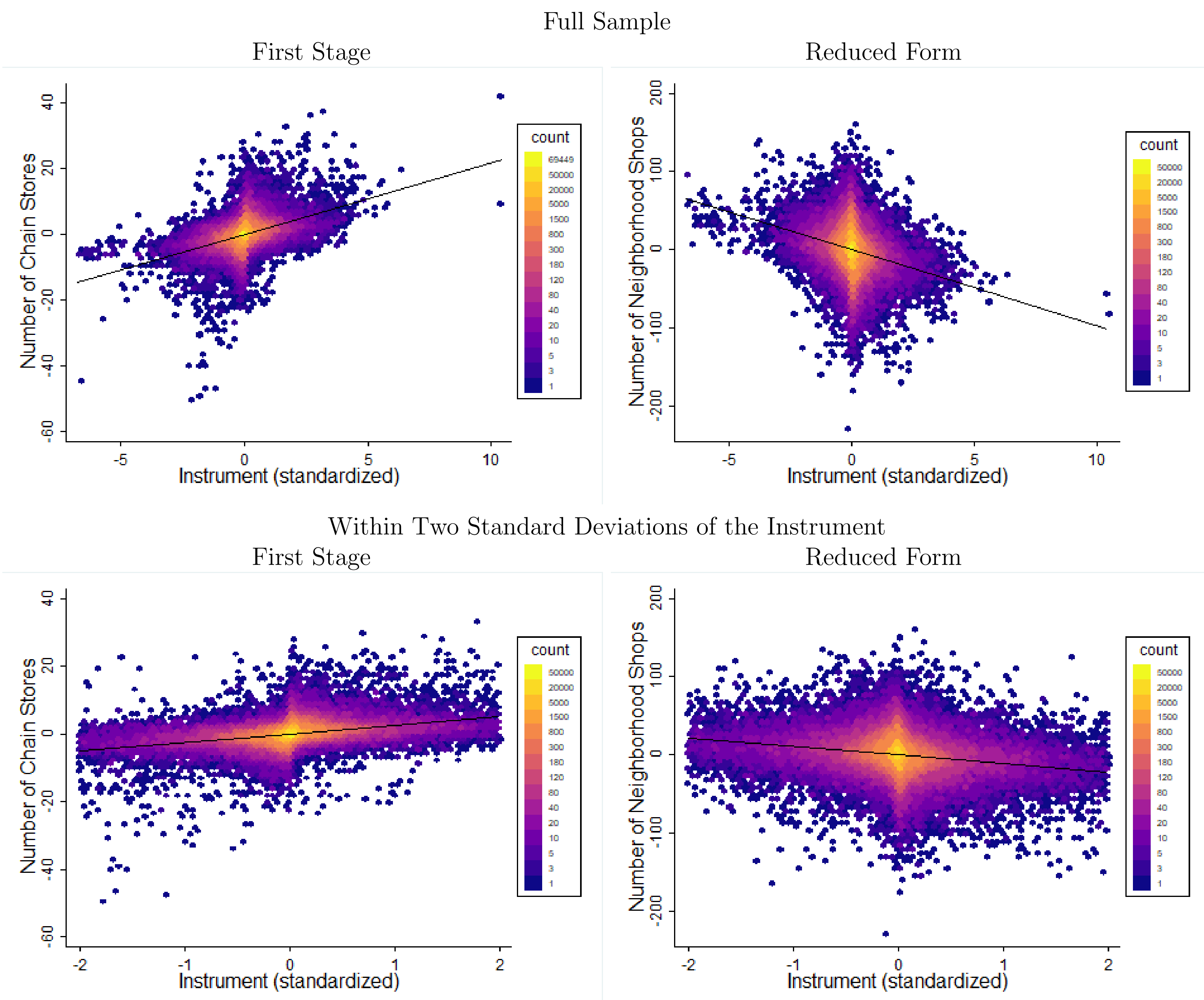


Figure A.9: Variation After Residualizing by Year-City and Neighborhood

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

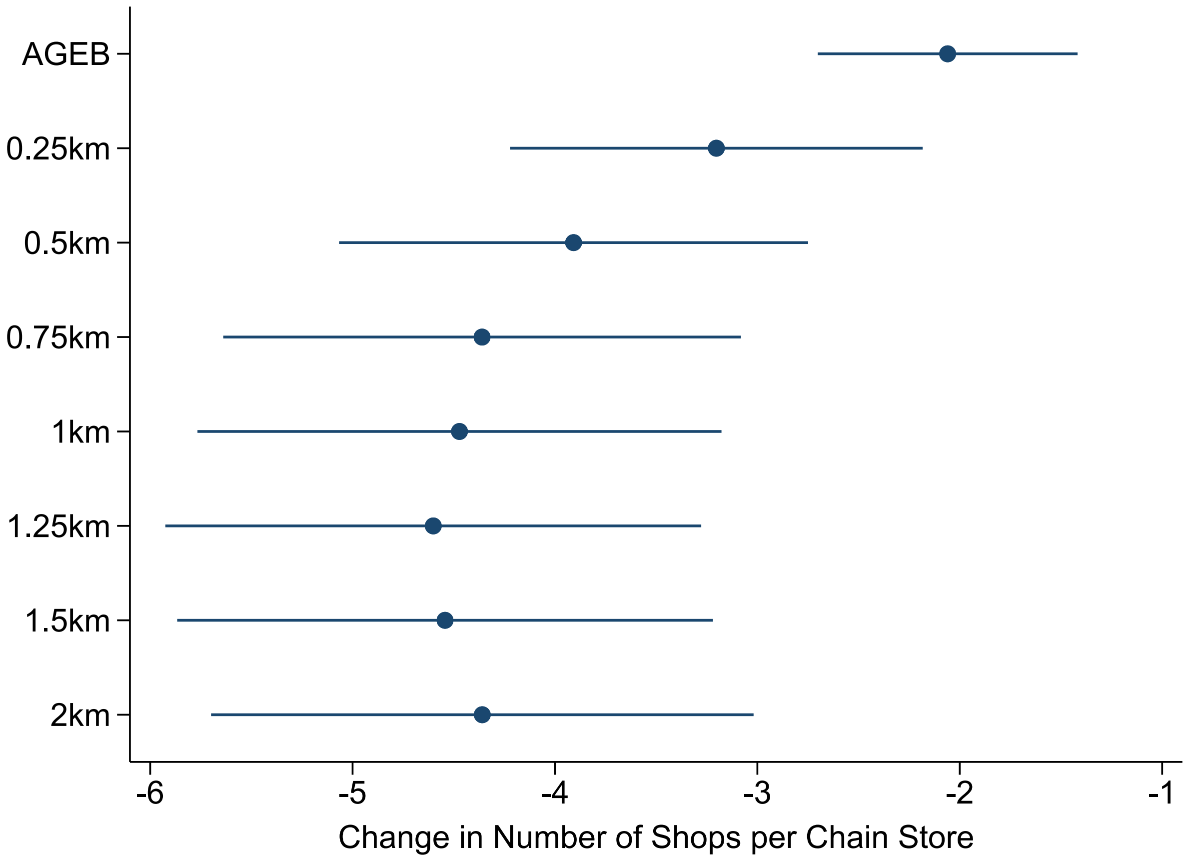


Figure A.10: Robustness - Alternative Neighborhood Definition

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 row 2, all the census tracts that are within 0.25km of a census tract center constitute a neighborhood.

Figure A.11: Hybrid Stores

Source: Google Maps
Note: The figure contains an example of a hybrid store. Hybrid stores share the same establishment type code as Chains, but different from Chains, the owners only have one store.

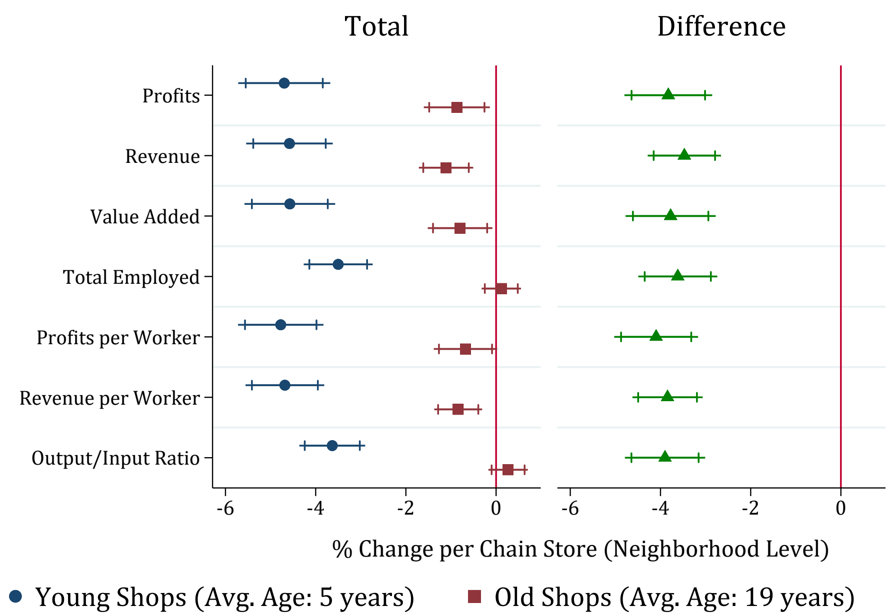


Figure A.12: Effects of Chains on Shops' Performance by Shop Age

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 average/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.

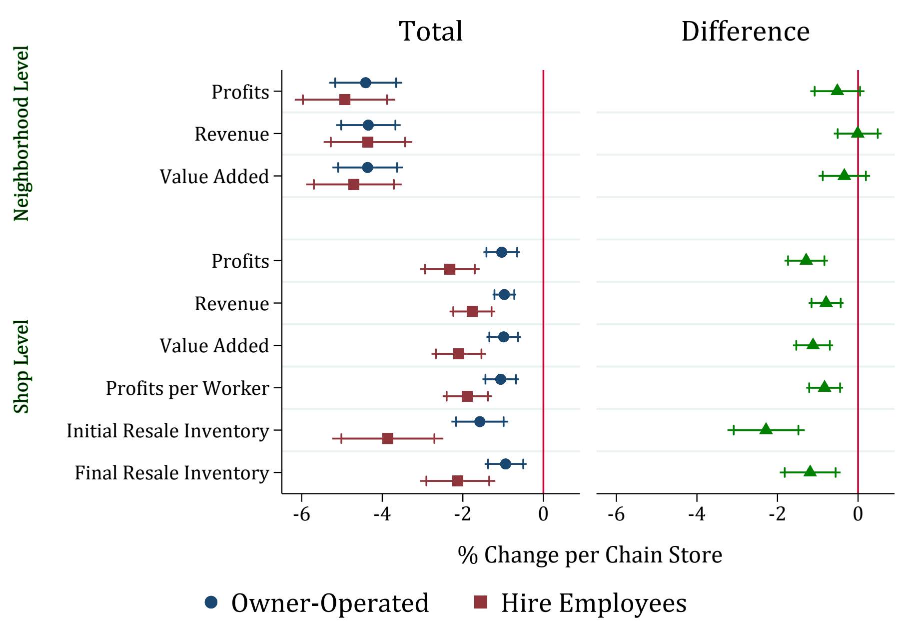


Figure A.13: Effects of Chains on Shops' Performance by Type of Management

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.

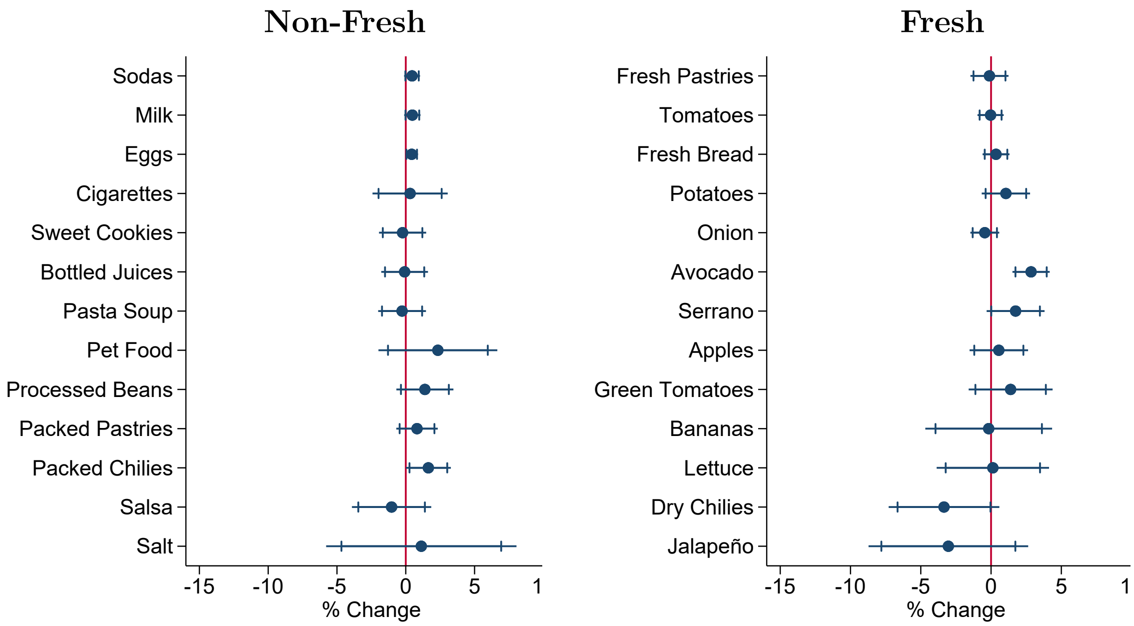


Figure A.14: Effect on Shops' Prices

Note: The figure displays the estimation of Equation 3 using 2SLS replacing the dependent variable with household-level price paid in pesos for each unit of the goods. The percentage change is computed by dividing the estimated effect by the household average product price in shops. The effects are for each additional chain store, and on average, there are 9 chain stores in each neighborhood. Goods are sorted from top to bottom by their share of shops' revenue. For non-fresh goods, sodas represent 13% of revenue and salt 0.2%. For fresh goods, sweet bread represent 3% of revenue and jalapeño 0.2%.

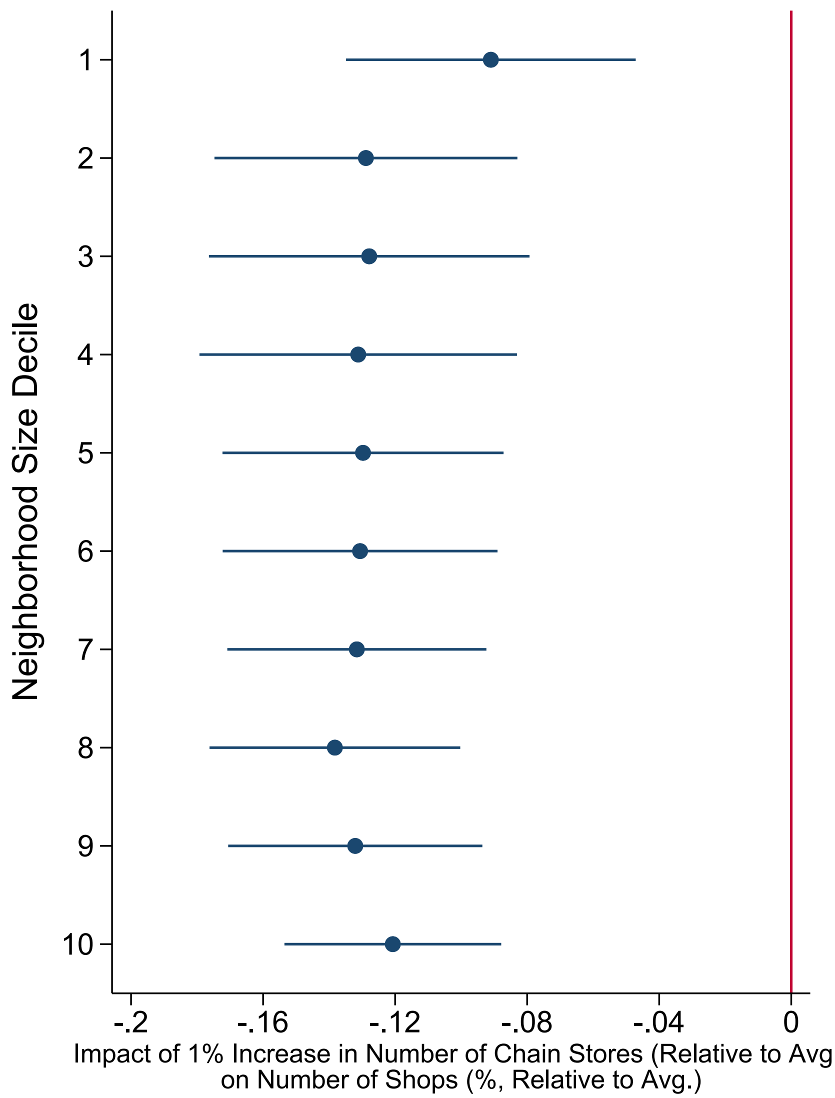
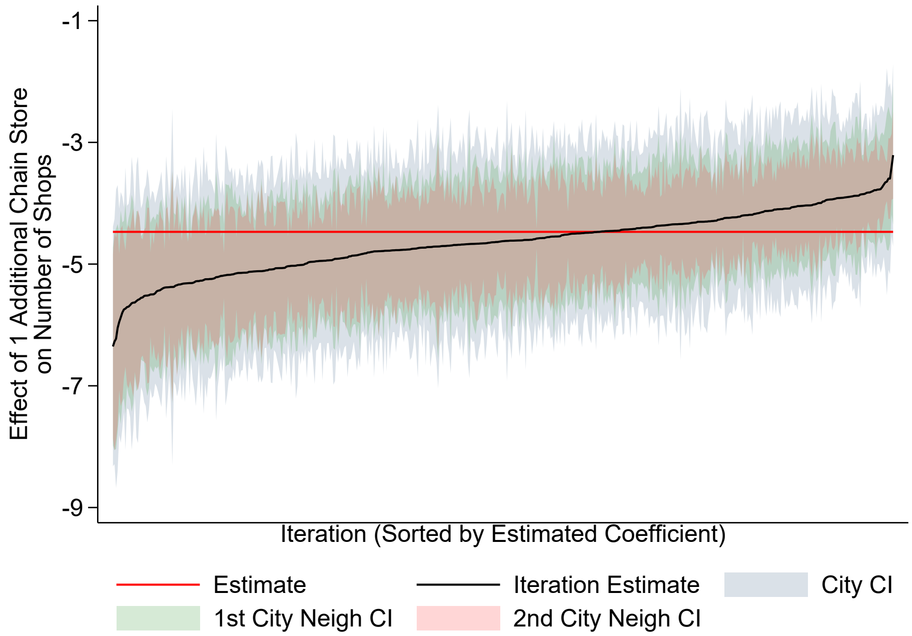
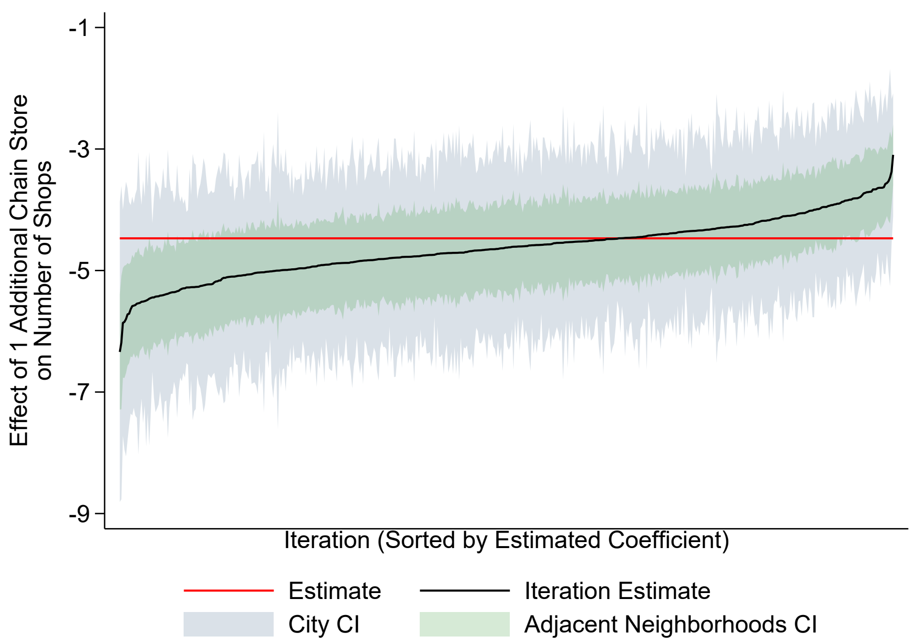


Figure A.15: Effects of Chains on Shops by Neighborhood Size

Note: The figure displays the estimation and 95% confidence intervals of Equation 3 using 2SLS but interacting both the instrument and the number on convenience chain stores with dummies for each decile of neighborhood sizes. The first decile contains the smallest neighborhoods. Deciles are constructed within city.



A) Spatial Correlation of Errors Across Adjacent Cities



B) Spatial Correlation of Errors Across Adjacent Neighborhoods

Figure A.16: Addressing Potential Spatial Correlation in Standard Errors

Note: The figure displays the estimation of Equation 3 using 2SLS. Each iteration contains a random sample of 5,000 markets, and in total there are 500 iterations in each figure. In Figure A), standard errors are clustered at the city level, corrected for the potential correlation of unobserved shocks across adjacent cities, and corrected for the potential correlation of unobserved shocks across 2^{nd}-degree adjacent cities. In Figure B), standard errors are clustered at the city level and corrected for the potential correlation of unobserved shocks across adjacent neighborhoods. 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: Zeroth Stage

If chains were to 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 and the number of chain stores that f has in city c. The coefficient of interest, β, tests for spatial correlation in the number of chain stores after controlling for firm-time, city-time, and firm-city fixed effects. I interpret this spatial correlation as economies of scale.

$$\#Stores_{f,c,t} = \eta_{f,t} + \mu_{c,t} + \zeta_{f,c} + \beta \#StoresNearbyTowns_{f,c,t} + \epsilon_{f,c,t} \quad (4)$$

Table 1: Same-Chain Economies of Scale

	Dependent Variable: # of Stores in City							
Nearby Cities:	2nd Degree Adjacent Cities				Adjacent Cities		3rd Degree Adjacent Cities	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Number of Stores Nearby Cities (same chain)	0.045***	0.047***	0.047***	0.046***	0.122***	0.115***	0.023***	0.022***
	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
Sample Size	416,704				416,398		416,398	
Clustered SE	City	City	City	City	City	City	City	City
Year, City, & Firm FE	Y							
Firm x City FE		Y	Y	Y	Y	Y	Y	Y
Year x Mun FE			Y	Y	Y	Y	Y	Y
Year x Firm FE				Y		Y		Y
R-squared	0.159	0.717	0.730	0.730	0.738	0.739	0.718	0.718
Within R-squared	0.105	0.150	0.152	0.111	0.176	0.140	0.115	0.073

Note: The table displays the estimation of Equation 4. 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.

The results presented in Table 1, estimated using equation 4, show that across all specifications, there is strong evidence of economies of scale: number of same-chain stores in towns nearby to town c are positively correlated with the number of same-chain stores in town c. Columns 1-4 use 2^{nd} degree neighbors (adjacent towns and towns adjacent to these), columns 5-6 use 1^{st} degree neighbors (adjacent towns), and columns 7-8 use 3^{rd} degree neighbors (adjacent towns and towns adjacent to these and towns adjacent to these). Column 4 is the preferred specification because it uses 2^{nd} degree adjacent cities (same as the IV), and includes all the fixed effects combinations. Economies of scale matter: 21 additional same-chain stores in nearby cities translate to one more store in the city – accounting for

11% of the variation in the number of stores each chain has in a city.[34]

Table 2: Cross-Chain Economies of Scale

	Dependent Variable: # of Stores in City						
Nearby Cities:	2nd Degree			Adjacent Cities		3rd Degree	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Number of Stores Nearby Cities	0.000***	-0.001***	-0.001***	-0.001***	-0.003***	0.000***	-0.001***
(different chain)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Sample Size	13,751,232			13,751,232		13,751,232	
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	0.060	0.060	0.696	0.060	0.696	0.060	0.696
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 5. 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.

The previous analysis tests the existence and importance of economies of scale in determining the time and city of the opening of same-chain stores. 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 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.

$$\#Stores_{f,c,t} = \eta_{f,t} + \mu_{c,t} + \zeta_{f,c} + \gamma_{g,t} + \delta_{g,c} + \beta \#StoresNearbyTowns_{g,c,t} + \epsilon_{f,c,t} \quad (5)$$

Economies of scale are firm-specific: the positive correlation in Table 1 dissipates when using the number of different-chain stores (competitors) in nearby cities, and the number of competitors in nearby cities account for less than 0.001% of the variation in the number of stores each chain has in a city. The results are in Table 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.

[34]The 11% is obtained by computing the within R-squared. It is the R-squared after demeaning each variable with respect to the fixed effects.