

Fragmented Markets and the Proliferation of Small Firms: Evidence from Mom-and-Pop Shops in Mexico*

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Abstract

Developing countries are characterized by the prevalence of small firms in the retail sector. We explain this phenomenon through a spatial model in which high transport costs lead to small effective market sizes and, consequently, to the proliferation of smaller and lower quality firms. We show that low costs of entry are key for this result. By obtaining a new, confidential panel of firm-level data surveying the universe of mom-and-pop shops in Mexico, we test the implications of our model. We exploit the deregulation of the Mexican gasoline market in 2017 as an exogenous shock on consumer transport costs. Where gas prices increased, the number of mom-and-pop shops differentially increased while their average size and quality fell. We give evidence of fragmentation and localized demand as the mechanism behind these effects. With our estimated model, we evaluate the welfare consequences of a licensing program in Mexico City which increased costs of entry for mom-and-pop shops. We show there are modest efficiency gains from having less stores in the market.

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1 Introduction

Small firms dominate developing countries (McKenzie, 2017). The disparity between the number of firms in developing relative to developed countries is especially noteworthy in the retail sector. In Mexico, there is one store for every 100 people; in Indonesia, one for every 80 people. In contrast, the United States has one store for every 2,200 people.¹ Stores are not just different in number but also in size. In Mexico and Indonesia, the market is dominated by mom-and-pop shops—small stores that are owner-operated—while in the US most shops are convenience stores (which tend to be located next to gas stations). We argue that an important contributing factor to the observed market structure in developing countries is that firms face small effective market sizes because consumer transport costs are high.

We study the role of consumer transport costs in explaining the number, size, and quality distribution of firms in developing countries. We develop a spatial model in which firms of different qualities choose to enter markets based on the demand they face. We show that in such a framework, increases in transportation costs reduce consumers' mobility and lead to fragmented and hyperlocalized markets. Because consumers prefer to shop locally after transport costs rise, firms that did not face enough demand to operate now find it profitable to operate. Importantly, they are able to enter the market because their fixed costs of entry are low enough to sustain profitability.

In the model, consumers decide where to shop depending on the transportation cost they have to pay to get to a store, the quality of the store at which they shop, and an idiosyncratic preference shock. Firms, meanwhile, decide whether to open a store depending on the share of consumers that will shop there and the fixed cost of entry they must pay.

The model guides our empirical analysis by providing comparative statics of how market structure changes as transport costs increase and by outlining the mechanisms at play. The model predicts that fragmentation increases the number of stores, decreases their average size, and decreases aggregate quality. Moreover, the model highlights that the effects of transport-cost shocks on market structure are mediated by consumers' elasticity with respect to transport costs and by the fixed cost of entry they must pay.

The model provides intuition as to why transport costs may matter more in a devel-

¹The number for Mexico comes directly from our main data set and includes only traditional stores (that is, nonchain establishments). The number for Indonesia comes from this news article: [The Presence of 3.6 Million Grocery Stores](#). Finally, the number for the US comes from the 2022 NACS/Nielsen Convenience Industry Store Count. Similar magnitudes emerge using Euromonitor's store count data for Traditional Grocery Retailers.

oping country than in a developed one. As transport costs increase and demand becomes fragmented (and market size shrinks), only firms with low fixed costs of entry find it profitable to enter. And the fixed costs of entry tend to be lower in developing countries for multiple reasons: to avoid paying taxes or regulatory fees, many firms do not register; and most firms operate within their owners' house to avoid having to purchase or rent a space. Rather than thinking of the fixed costs in monetary terms, we can think of them as the opportunity cost of shop owners' time. In this framing too, fixed costs are lower in developing countries, as reflected by fewer wage-employment opportunities.

The model also sheds light on how higher transport costs reduce aggregate quality in the retail sector. Market fragmentation deters high-quality firms with high fixed costs of entry from opening and leads to an equilibrium with many small firms.² This is because higher-quality firms need a certain market size to operate and take advantage of economies of scale, which is not possible when consumers have limited mobility and effective market sizes are small.³

To test the predictions of our model, we focus on the traditional food retail sector in Mexico, which is mostly composed of mom-and-pop shops. This is an economically meaningful sector to study and one well suited for our analysis for a variety of reasons. First, as in many other developing countries, the traditional retail sector represents an important share of the economy: it contributes 7% to Mexico's GDP, employs over 83% of workers in the food and beverage sector, and represents 15% of all micro firms. Second, it is ideal for analyzing how market structure is affected by transport costs since stores' main margin of differentiation is location. As we explain in Section 2, both product-quality and price channels are shut off in this sector. Finally, the sector represents an important share of household expenditures. For the average household, food is the biggest source of expenditure, and most of that spending—around 70%—occurs in traditional stores.

We overcome the common data-limitation challenge of the service sector—namely, that it includes many informal firms—by partnering with one of the biggest suppliers to mom-and-pop shops. Our high-frequency and spatially detailed data set consists of a panel of 1.5 million firms that includes information on all purchases they made from our data partner from 2017 to 2020. Our novel data set allows us to view the universe of firms in the traditional food retail sector, regardless of their formality status, since every store

²We show in the data that there is a positive correlation between low fixed cost of entry firms—as measured by the opportunity cost of opening a store, namely wages in paid employment—and quality. In the model we assume the fixed cost of entry and quality of each firm come from a joint distribution.

³A similar point about the relevance of market sizes and growth is made in [Goldberg and Reed \(2020\)](#) and in [Jensen and Miller \(2018\)](#)

carries products from our upstream supplier and every household buys from them.⁴ With this data set we overcome the usual trade-off between having detailed but low-frequency census data and having to collect our own data, which would be expensive and cover only a fraction of firms.

To see how changes in transport costs affect market structure, we leverage exogenous municipality-level variation in gas prices following the deregulation of the gasoline market in the last quarter of 2017. Before the deregulation, the government subsidized gas prices and charged the same price at every pump in the nation, regardless of logistics costs. To ease endogeneity concerns stemming from the possibility that gas price changes are correlated with changes in local economic conditions, which also affect market structure, we instrument gas prices using distance to the closest gasoline distribution center. The intuition behind the instrument is that once the government allowed prices to fluctuate, gas stations that were closer to distribution centers experienced less of a price hike than those farther away because subsidized prices did not reflect differences in logistics costs. Indeed, our first stage reveals that municipalities that were farthest from a distribution center experienced close to a 5% gas price increase relative to municipalities closest to distribution centers. Importantly, the number of distribution centers did not endogenously change, nor did their location.

In the reduced-form results, we show that municipalities that were farther from distribution centers experienced an increase in the number of mom-and-pop shops. This effect is primarily explained by new entrants rather than by incumbents not exiting the market, which supports the hypothesis that markets were fragmenting. A decrease in firm exit would have suggested that labor-market conditions were changing for store owners, making it more desirable to stay in the business. We also find a relative decrease in the average size of mom-and-pop shops. This decrease comes mostly from a business-stealing effect of entrants on incumbents (around 75% of the effect); the rest of the effect is explained by entrants' smaller size and by a decrease in demand, especially in the first three quarters after the gas price shock.

An important prediction of the model is that firms enter the market even when local demand is low if their fixed costs of entry are sufficiently low. This has implications for the type of firm that enters if quality and fixed costs of entry are positively correlated. While we do not impose this in the model as an assumption, we can empirically see which types of firm enter. To do so, we exploit our panel-level data and estimate firm-level quality measures using our full sales data set with firm fixed effects and controlling for age

⁴Kantar reports that the brand our data provider sells has a 98.9% penetration rate in Mexican households.

of firm and local demand shocks. We find that entering firms are of lower quality in municipalities more impacted by the gas price shock. We do a similar exercise with a proxy for fixed costs of entry and find that entrants in the most affected municipalities have lower fixed costs of entry. Taken together, these results suggest that there is a positive correlation between quality and fixed costs and that entering firms are of lower quality.

We propose two mechanisms through which gas prices affect transport costs and consequently the market structure. In the first, gas price rises increase the cost of driving to a supermarket relative to walking to a mom-and-pop-shop. While this mechanism is important, only 26% of municipalities have a supermarket and our results on market-structure changes persist even when we restrict our sample to places without supermarkets. The second mechanism is that when gas prices increase, overall mobility within a city decreases, causing people to shop closer to where they live.

We use data from National Statistical and Geographic Information System's (INEGI's) Household Expenditure and Income Survey, which is conducted every two years and contains information on where people shop and what they buy, among other things. We focus on food and transportation expenditures to explore each mechanism. Using the same gas price shock and the same instrument as before, we find evidence that households substituted from supermarkets to mom-and-pop shops in places where gas prices increased more as indicated by where they shop for groceries. We also find that in places where gas prices increased more, households reported higher frequency of shopping, which suggests more shopping at mom-and-pop shops and less at faraway supermarkets.

To test whether the gas price hike decreased mobility within cities, we look at gasoline and public transportation consumption on the extensive and intensive margins. We find a relative decrease in the number of gasoline consumers (extensive margin) and in liters of gasoline consumed (intensive margin). We also see an increase in the share of people using public transportation and an increase in public transportation expenditure, suggesting that people became less mobile because of the shock. To look at substitution between mom-and-pop-shops, we simulate the location of 1,000 random households in each municipality and calculate the average distance traveled to the closest mom-and-pop shop in every period. We find a decrease in distance traveled in municipalities that experienced a larger gas price increase.

We find evidence against other potential mechanisms when examining the evolution of nominal wages, employment, relative prices, and changes by the upstream supplier. If wages were falling in places where gas prices rose, households would have had a stronger incentive to open a mom-and-pop shop to make up for lost income. We look at the evolution of wages using data from the Mexican Institute of Social Security (IMSS) data, which

contains the universe of formal workers, and find no change. Separately, we use confidential administrative data obtained from INEGI on prices at the store-by-barcode level from a sample of stores and find no evidence of prices changing differentially. Even if wages were not changing, total employment might have changed, making unemployment more likely. Again using IMSS data, we check for falling employment and find no evidence of it. A concern related to prices is that relative prices in modern versus traditional stores changed.⁵ Using the same price data and leveraging the information on what type of store a price was recorded at, we do not see any changes in prices at traditional versus modern stores. Finally, if the upstream supplier were also affected by changes in gas prices, we would expect this to bias against finding a result because as transport costs increase, the upstream supplier would want to visit fewer stores to lower costs.

In the second part of the paper, we estimate the relevant parameters to solve the model: the elasticity with respect to transport costs, and the parameters of the bivariate distribution of quality and fixed costs of entry. While the traditional way of estimating this elasticity requires information on where consumers live and where they shop, which is hard to come by in developing countries, we propose a novel estimation strategy that uses indirect inference by exploiting the spatially detailed high-frequency nature of our data. We show that the geographic decay of the effect of entry by one firm on incumbent firms' sales can be used to estimate this parameter. We find that entry has a business-stealing effect that extends only to stores within 300 meters of the entrant, suggesting a high elasticity with respect to transport costs.

To estimate the joint distribution of quality and fixed costs, we use the method of simulated moments. Using the observed equilibrium (that is, looking at data on all existing firms in the market), we obtain the relevant moments for the bivariate distribution. The parameters obtained directly from our data describe the mean and standard deviation of entrants but not the underlying distribution of potential entrants. To remove this bias, we use observed moments as our starting parameters for the bivariate lognormal distribution, obtain many draws, and look at the set of operating firms according to our model. We calculate the distance between the model's moments and the empirical moments and minimize that distance. We find a positive correlation between quality and fixed costs. This has implications for market structure, as the stores that enter are on average of lower quality. This is because markets are small, and only firms with low fixed costs of entry find it profitable to open.

In the last part of the paper, we evaluate a policy in Mexico City that attempts to

⁵For example, this could happen if modern stores are faster at adjusting prices and pass onto consumer the increase in gas prices.

regulate mom-and-pop shops by requiring them to hold a certificate of operation. With the program, store owners are expected to show a set of documents and pay a fee for the certificate. Effectively, the program increases fixed costs of entry. With our estimated model, we model this “tax” as additive to the fixed cost of entry (implying that it hurts small stores) and rebate it back to households. We calculate a welfare gain of 1.4% from having fewer stores in the market due to an increase in producer surplus (less business stealing). The maximum gain in welfare from decreasing the number of stores in the market is 2% relative to baseline welfare (that is, zero tax), which implies the equilibrium is close to the efficient number of stores.

Our paper contributes to various strands of the literature. First, it relates to a large literature on constraints on firm growth in developing countries. Various factors have been explored, including lack of access to credit markets (De Mel et al., 2008; McKenzie and Woodruff, 2008; Banerjee et al., 2019), barriers to hiring (Carranza et al., 2021; Bassi and Nansamba, 2022), lack of business training (Field et al., 2010; Mano et al., 2012; De Mel et al., 2014; Blattman et al., 2016; McKenzie, 2017), poor contract enforcement (Iyer and Schoar, 2015; Boehm and Oberfield, 2020), and high cost of formalization (McKenzie and Sakho, 2010; Campos et al., 2018). We argue that focusing on the supply side as a means of boosting growth and productivity is not enough. Demand-side frictions can impact market structure as well.

We thus join a small but growing number of papers that argue that demand-side factors matter for market structure, productivity, and growth (Syverson, 2004a,b; Lagakos, 2016; Jensen and Miller, 2018; Goldberg and Reed, 2020). Our work is most closely related to two papers that look at the effect of effective market size on the distribution of firm size. You (2021) looks at Boston’s rapid electrification of the streetcar system in the late 19th century and finds a decrease in the share of sole proprietorships. In contrast to You, we focus on a modern-day developing country and are able to speak to the welfare consequences of having fewer stores. Meanwhile, Jensen and Miller (2018) study the role of information frictions in limiting firms’ potential market size and competition in the boat-building industry in Kerala, India. In contrast to them, we focus on transport costs as a barrier to market size. Additionally, our data allow us to look at an entire industry that is economically meaningful and similar to other middle-income countries, where an important share of the population is employed in the retail sector and specifically in small firms (Hsieh and Olken, 2014).

Second, we contribute by including a model that builds on a long literature, originating in Hotelling (1929) and Salop (1979), in which space plays an important role in product differentiation. Building on insights from this literature, our model allows for

an arbitrary geography and firm heterogeneity, while still being tractable. Our model captures the welfare trade-off between consumers' taste for variety (that is, having more stores in the market) and the business-stealing effect of an extra shop. To solve the model, we use a novel estimation strategy for the key elasticity we are interested in.

Third, we can look at municipality- and firm-level outcomes thanks to the novel data we use. This goes beyond previous papers, which focus on regional outcomes as a response to transport-cost shocks.⁶ Additionally, we speak to the general literature on the role of transportation and find supporting empirical evidence that high transport costs can be an important constraint on growth and productivity (Hsieh and Klenow, 2014).

Finally, we speak to the literature on firms in the retail sector (Atkin et al., 2018; Higgins, 2018; Marcos, 2022; Anderson et al., 2022) and contribute to the field's understanding of these firms through the rich data we have. In particular, we are able to focus on the traditional food retail sector and understand the nature of competition between firms.

In the next section we give a brief overview of our setting. In Section 3 we lay out our spatial model and discuss the comparative statics it yields. In Section 4 we describe the exogenous variation in consumers' transport costs and the rest of the data we use in our empirical estimation. In Sections 5 and 6 we present our empirical strategy and results, respectively. In Section 7 we describe our estimation strategy for the relevant parameters. In Section 8 we evaluate the welfare implications of a policy in Mexico City that imposed higher fixed costs of entry. We conclude in Section 9.

2 Setting

We focus on the traditional food retail sector in Mexico, which represents 15% of all micro firms (INEGI 2010) and accounts for 43% of the median household's food expenditure (ENIGH 2016). We begin by describing our setting and then discuss the exogenous variation in transport costs that we use for the empirical analysis.

While the overall food retail sector in Mexico is composed of three distinct distribution channels—modern (supermarkets and convenience stores), traditional (mom-and-pop shops, street vendors, and specialty shops such as tortillerias), and electronic (online shops)—the vast majority of sales, stores, and employment are in the traditional sector. This is not unique to Mexico, but rather a consistent characteristic of developing countries.⁷

⁶For example, Banerjee et al. (2019) examine the effect of access to transportation networks on regional economic outcomes in China; Donaldson (2018) looks at the effects of a large infrastructure project in Colonial India on regional price dispersion and welfare.

⁷Nielsen (2015) documents that 46% of all food and beverage purchases happen in the traditional sector

Traditional sector: mom-and-pop shops in Mexico. In this paper, we focus on the most prevalent type of store in the traditional sector: mom-and-pop shops (Figure 1). There are around 800,000 of them, operating every month in virtually all localities in the country. To put the number in perspective, there is on average one store for every 100 people. These shops open and close frequently, with an annual entry rate of 16% and an exit rate close to 15%.⁸ The high entry rate and the fact that over 50% of store owners report having opened their shop in their own house suggests that costs of entry are low.

The highest cost of operating a mom-and-pop shop is the purchase of products as shown in Figure 2. The other categories reveal how these businesses operate. They buy everything in cash and have little access to credit (they do not report having to make interest payments). Most of the products they sell are delivered by the suppliers directly to their stores (low gasoline expenditure). Moreover, the upstream supplier comes back at least once every two weeks to look at a store's inventory to replace any products that are close to their expiry date. Apart from helping with managing inventories, the upstream supplier also provides shelving units, provides posters for marketing, and sometimes even pays for the awning. Store owners operate on their own homes and thus do not incur rent costs; they pay virtually no taxes; and they are owner-operated or employ unpaid household labor. Their biggest costs apart from their inputs are the utilities, such as gas, water, and electricity, that are needed to keep the food cool.

This industry is well suited for analyzing how market structure is affected by transport costs since stores' main margin of differentiation is their location. Households report location as their number one reason for shopping at these stores (COFECE, 2020), and store owners report demand as one of the main factors in their location decision (ENAPROCE 2018). Stores sell homogeneous goods: soda, bread, milk, cigarettes, and beer. Most of the products they sell are branded, so product quality is the same across stores, thus removing this margin of competition. Moreover, because prices are posted on product packages (and many times on shelving units and posters provided by the upstream supplier), the price-competition margin is also removed.⁹

For households, mom-and-pop shops represent a large share of expenditure on food.¹⁰ Expenditure in the traditional food retail sector ranges from 82% in the lowest decile to

in developing countries while this number is 1% for developed countries.

⁸Our estimates are in line with other papers that report entry and exit rates for informal and micro enterprises in developing countries. For example McCaig and Pavcnik (2021) and McKenzie and Paffhausen (2019). They are higher than rates for developed countries. For example, using US manufacturing census data Dunne et al. (1988) find annual entry rates of 14% and exit rates of around 12%.

⁹Over 80% of firms report fixed markups, ENAPROCE.

¹⁰Expenditure on food as a share of total expenditure ranges from 54% for households in the lowest decile of the income distribution to 29% for those in the highest decile

61% in the highest decile, as shown in Figure 3. Within the traditional retail sector, mom-and-pop shops represent around 50% of expenditures. The opposite pattern is observed for expenditure in modern supermarkets, households in the lowest income decile spend the least in supermarkets while this number increases to almost 15% for those in the highest decile of the income distribution. A very similar picture appears if we look at expenditure in the traditional sector globally as seen in Appendix Figure A.1.

Although mom-and-pop shops are an important part of the economy—employing close to two million people, contributing 7% of the country’s GDP, and representing 15% of all micro firms—data limitations have made it hard to study their characteristics, how they respond to shocks, and what their market structure is. To surmount these limitations, we partnered with one of the largest upstream suppliers of mom-and-pop shops in Mexico and obtained a monthly panel of the 1.5 million firms operating from 2017 to 2020. Our partner company, together with seven other upstream suppliers (suppliers of chocolate, soda, milk, beer, and cigarettes), represents 90% of total sales at mom-and-pop shops (Anpec, 2013). The relationship between our data provider and the mom-and-pop shops is simple: once someone decides to open a store, the upstream supplier delivers products directly to the shop at least once every two weeks. The advantage of the data set is that because virtually everyone buys from our supplier, we obtain the universe of all firms. In Appendix Figure A.2 we show the representativeness of the data by comparing our sample with the mom-and-pop shops recorded in the economic census.

3 Spatial Model

The economy consists of a city with N blocks indexed by $i, j \in \{1, \dots, N\}$, each with M_i consumers. We assume that, on each block, one person has property rights to land on which to potentially open a mom-and-pop store. A store is characterized by the block j on which it is located, the quality of service it provides, and the fixed costs of entry it must pay to enter the market.¹¹ All consumers consume one unit of a bundle of goods with fixed price p across the city. We argue that this assumption is valid in the context of traditional stores since most products sold come from branded goods with posted prices on the packaging.¹² Finally, we assume that on the outskirts of the city there is an ex-

¹¹This implies that there is at most one store per block, which is without loss of generality since one can make the blocks as small as one wants.

¹²We also provide evidence in favor of this assumption using two distinct sources of data. Using the National Survey on Productivity and Competitiveness of Micro, Small and Medium Enterprises (ENAPROCE) conducted by INEGI in 2018 we see that 87% of store-owners report having a fixed price. Moreover, Figure A.3 displays kernel estimates of the log price distribution pooled over store format and months. Log prices

ogenously placed supermarket at which consumers can shop for the same good. Thus, consumers can either buy closer to home in a mom-and-pop shop or exercise the option of going to a supermarket.

3.1 Consumer Side

Consumers are distributed across blocks within the city, where the blocks are denoted by i . Consumers at each location i have an inelastic demand for a homogeneous bundle that they buy at a store located on block j . The utility received by a consumer living in i and buying the good on block j is characterized as follows:

$$u_{ij} = \frac{\gamma_j \epsilon_{ij}}{p \tau_{ij}}$$

Here, τ_{ij} is the cost the consumer pays to travel from i to j , γ_j is the quality of store j , and $\epsilon_{ij} \sim \text{Frechet}(\theta)$ represents idiosyncratic factors on the basis of which a consumer who lives in i might choose to buy the good on block j .¹³ Consumers in neighborhood i choose the store j that maximizes their utility. Given our distributional assumption about ϵ_{ij} , we can show that the share of consumers from i that shop on block j is as follows:

$$s_{ij} = \frac{\left(\gamma_j \tau_{ij}^{-1}\right)^\theta}{\sum_{j'} \left(\gamma_{j'} \tau_{ij'}^{-1}\right)^\theta} \quad (1)$$

Here, $j' \in \Omega$, and Ω is the set of all the operating stores. Since the price is fixed, it drops out of the above expression. The parameter θ represents the elasticity of demand with respect to transport costs and quality.

Equation 1 implies that consumers are more likely to patronize stores with higher quality that are closer to them. That is, they value convenience and quality.

Total demand at store j coming from consumers located on block i is given by $D_{ij} = M_i s_{ij}$, assuming $w_i = 1 \quad \forall i$ and a mass of M_i consumers on block i . Thus, total demand

are expressed as deviations from the month's average. All the variation observed is within month. From this figure, one can see that there is little variation in prices across traditional stores, especially when compared to prices in modern stores. The density plots become even tighter for traditional stores if we look at variation within month-state and tighter for variation within month-municipality (Figure A.4 and Figure A.5 respectively, in the appendix).

¹³One can think of τ_{ij} as decreasing the effective wage people obtain because it reduces the time one can spend working. Consumers earn an exogenous income w_i . The budget constraint is: $\frac{w_i}{\tau_{ij}} = pc_{ij}$. Utility is linear in consumption and quality of buying in store j is γ_j : $u_{ij} = \gamma_j c_{ij} \epsilon_{ij}$ with an idiosyncratic shock.

faced by firm i is given by the sum across all blocks from which consumers could come:

$$D_j = \sum_i D_{ij}$$

3.2 Supply Side

On each block, an individual with a property right can use their house to open a mom-and-pop shop. Firms are characterized by their quality γ_j and their fixed costs of entry F_j . This quality measure represents all nonprice productivity differences across shops.¹⁴ If a store opens, it will earn a fixed markup over marginal cost, μ , that is set by the upstream supplier and pay a fixed cost that varies across blocks F_j . Profits are given as follows:

$$\pi_j = \mu D_j - F_j$$

We assume that on one block indexed by K there is a modern supermarket.¹⁵ This store differs from mom-and-pop shops in that it has higher quality and higher fixed costs of entry. That is,

$$\begin{aligned} \gamma_k &> \gamma_j, \forall j \\ F_k &> F_j, \forall j. \end{aligned}$$

Additionally, we assume the supermarket is not endogenously making an entry decision but simply takes demand as given and always operates. A consumer might prefer to go to the supermarket because of the higher quality it provides.¹⁶

3.3 Equilibrium

The equilibrium in the city is given by the decision of the individual with property rights in each block to open or not open a mom-and-pop-shop , in such a way that $\pi_j \geq 0 \quad \forall j$.

¹⁴We think of the quality measure as a store having more variety, longer hours of operation, better customer service and nicer stores.

¹⁵We select a low density block for the supermarket placement to capture the fact that supermarkets tend to be in the outskirts of the city, farther away from where people live.

¹⁶While we do not allow prices to be different in mom-and-pop shops and supermarkets, the quality measure is enough to capture differences between the two type of shops.

The equilibrium is characterized by the set of blocks that open their stores,

$$\Omega \equiv \{j \in \{1, \dots, J\} : \pi_j > 0\},$$

and the blocks that do not,

$$\pi_j < 0 \quad \forall j \notin \Omega.$$

3.4 Transport-Cost Shock

In this section, we describe how a gas price shock maps to the model. We show that as transport costs increase, the number of stores increases and aggregate quality falls. We also show the roles that F , the fixed costs of entry, and θ , the elasticity with respect to transport, play in reaching this result and discuss each one.

3.4.1 Mapping the transport-cost shock to the model

We explain in detail the exact source of variation we use for our empirical strategy in Section 4; here we simply describe how to think of the gas price increase in terms of the model.

When gas prices increase, it affects consumers' choice of where to shop through two distinct channels. First, the price increase changes general mobility patterns within a city by making car trips more expensive. For example, if people change their means of commuting from cars to public transportation, then they are less likely to patronize stores that are far from their homes and more likely to buy locally to avoid having to carry their groceries. This means that overall τ_{ij} increases $\forall i \neq j$. Second, by modifying the cost of going to the supermarket.

To see how the change in gas prices affects market structure, we lay out how it affects each margin: (1) the effect on mobility patterns and (2) the effect on the price of shopping at a supermarket.

Commuting costs. Gas price increases also increase the general costs of reaching any block. When gas prices increase, costs of transporting oneself to any block become more costly since the cost of the fastest way of commuting (a car) has increased. If people change the way they move, by either using public transportation or walking, then they become less mobile within the city, so they visit fewer blocks on their commute and become less likely to shop far from home.

As costs of transport to any block increase such that $\tau_{ij} \rightarrow \infty$ for every $i \neq j$, consumers prefer to stay on their own block i to do all their shopping. Quality is no longer relevant, and stores have a captive consumer base regardless of their quality. Markets fragment, demand becomes hyperlocalized, and mom-and-pop shops enter. Conversely, when transport costs decrease such that $\tau_{ij} = 1 \quad \forall i, j$, everyone decides to patronize the supermarket, where quality is higher.

If increases in gas prices only operate through decreased mobility, we expect the following effects:

1. **Prediction 1:** The number of mom-and-pop shops will increase, as new entrants seek to satisfy the now-fragmented demand.
2. **Prediction 2:** There will be no change in aggregate demand faced by mom-and-pop shops since people are simply substituting between mom-and-pop shops.

Cost of shopping at a supermarket. Recall that a modern supermarket is located on block K and customers face costs τ_{iK} to get to it. As is standard in the literature ([Zárate, 2019](#); [Tsivanidis, 2019](#)) we define $\tau = \exp(\delta_\tau * \text{distance}_{ij})$. In this way, a proportional gas price change modifies the term inside the exponential meaning that the gas shock will differentially affect blocks depending on their distance to a supermarket. Blocks close to supermarkets will barely be affected while blocks far away will be affected more $\hat{\tau}_{ik} > 0 \quad \forall i$, where $\hat{\tau}_{ik} \equiv \frac{d\tau_{ik}}{\tau_{ik}}$. Then, as a first-order approximation, the change in the demand for any given firm j is given as follows:

$$\hat{D}_j = \theta \sum_i \omega_{ij} s_{iK} \hat{\tau}_{ik} \tag{2}$$

Here, $\omega_{ij} \equiv \frac{M_i s_{ij}}{\sum_{i'} M_{i'} s_{i'j}}$ is the share of all sales by firm j that come from consumers located at i . The change in demand for a given firm j is given by how many consumers the mom-and-pop shop is able to take from the supermarket. This is governed by how sensitive consumers are to transport costs (θ), what share of the demand at store j comes from i (ω_{ij}), the share of consumers from i that originally shopped at the supermarket on block k (s_{iK}), and how much the transport cost changes ($\hat{\tau}_{ik}$).

It is easy to see that as $\hat{\tau}_{ik}$ increases, demand on block j increases, leading to more potential entry. Moreover, Equation 2 predicts how effects are distributed across space. Demand at mom-and-pop shops that are either very far from or very near a supermarket should be less affected by a gas price increase than those at an intermediate distance. To see this, notice that a block j that is very far from the supermarket has few people initially

buying on block K such that $s_{iK} \approx 0$, while for a block j very close to the supermarket the increase in gas prices is not relevant $\hat{\tau}_{iK} \approx 0$. It is only for intermediate-distance blocks that the three terms that make up Equation 2 are positive and not close to zero. Thus, we expect an inverted-U-shaped effect of entry with respect to distance.

If increases in gas prices only operate through the substitution channel (that is, people switching from supermarkets to mom-and-pop shops), then we expect the following impacts on mom-and-pop shops:

1. **Prediction 1:** Aggregate sales at mom-and-pop shops and number of mom-and-pop shops will increase in places where gas prices increase more, reflecting the new demand from those who switch from supermarkets to mom-and-pop shops.
2. **Prediction 2:** The effects will have an inverted-U shape with respect to distance from block j to a supermarket. We expect the largest effects to be concentrated in the middle.

3.4.2 Magnitude of effect

Two variables are crucial to determine the effects of increases in transport costs on the number of firms: (i) the elasticity with respect to transport costs represented by θ in our model; and (ii) the fixed costs of entry represented by F . The first one is relevant because under high values of θ even small increases in transport costs can modify where consumers shop. The second one matters because only in a scenario where fixed costs of entry are low are firms able to enter when market sizes are small.

While we don't have a particular stand on why θ would be different in developed vs developing countries we do believe that low fixed costs of entry (F) are characteristic of developing country. In our particular context many different factors suggest that entry costs are low: most shops are informal and thus never have to pay government fees, upstream suppliers help shop-owners with the necessary infrastructure to set up their shop (things like shelves and refrigerators), and over half of all stores open in the owner's own property limiting how much they have to spend on securing real estate space. Many of these same characteristics generalize to other stores within retail and to other countries. In this sense, low costs of entry suggest that the effect of transport costs on market structure might be more relevant for explaining the observed patterns in developing countries relative to developed ones.

In the appendix, we show simulations of the effects on entry, profits and quality, of symmetrically increasing transport costs τ for different levels of θ and F . Appendix Figure 6(a) and 6(b) show that as θ increases—that is, consumers are more sensitive to trans-

port costs—entry of new firms happens sooner. And as more firms enter, average profits go down and average quality goes down, respectively. The same pattern emerges in Appendix Figure 7(a) and 7(b), as F becomes lower, more shops are able to enter the market.

3.5 What is the effect of entry?

The simple model that we have laid out in this section gives us intuition of the welfare effect of having an additional mom-and-pop shop in the market. We briefly discuss the effects on consumers and producers and present the full derivation of welfare expressions Section 8.

Note that in our model stores differentiate themselves by the quality they offer and the block in which they enter. In this sense, consumer welfare is fully captured by market access which depends on the stores that exist in equilibrium. If a new store enters—regardless of the quality of the store—consumer surplus increases.¹⁷ The closer the new store is to the consumer the bigger the gain.

Producer surplus on the other hand is given by the sum of profits of all stores in the market. An additional store opening hurts other shop owners to the extent at which it can steal business away from them. Ex-ante there is no reason to assert that entry increases or decreases welfare. For example, imagine the extreme case where opportunities for wage employment are nonexistent such that $F_j = 0 \quad \forall j$. In this case, the social planner would want to have one store in every block to maximize consumer surplus. As soon, as we move away from a setting with fixed cost of entry equal to zero, there is a trade off from increasing variety (i.e. having more stores in the market) and a business stealing effect.

4 Transport cost shock and Data

4.1 Transport cost shock

In order to see how transport costs affect market structure we exploit the deregulation of the gasoline market in the last quarter of 2017. As part of the Energy Reform approved by congress in 2013, the government announced that it would stop subsidizing the price of gas, moving away from a national uniform price towards a price that reflected its real cost. The deregulation happened in different stages. The first change occurred in January of 2017 when price bands where introduced by regions to gradually move towards a

¹⁷Quality is not relevant since even in the case where the store that enters is of lower quality than existing stores, consumers can always choose to shop at a higher quality store. They only switch if they are better off.

completely free market. By the third quarter of 2017 states had to get rid of all regulations and allow prices to freely fluctuate. Figure 4 shows the evolution of gasoline prices at the municipality level in our sample.

When the deregulation happened, gas prices increased differentially across municipalities. An important part of this variation came from the fact that logistics costs were incorporated for the first time. Municipalities that were closer to distribution centers experienced less of a price hike than municipalities that were further away. We leverage this fact to construct an instrument based on the average distance from every gas station in a municipality to the closest distribution center which can be a refinery, a port or the US border.

This shock affected households across the whole income distribution. As can be seen in Figure 5 even in the lowest income decile over 20% report spending money on gasoline in the past month (check how question is framed). This number goes up to almost 80% of households in the last decile of the income distribution.

4.2 Data

We combine our novel mom-and-pop shop level data with a rich collection of microdata from different sources which we describe in this section.

Mom-and-pop shop. To look at changes in market structure we use a monthly panel of the universe of mom-and-pop shops from 2017-2020. We obtained this confidential data by partnering with one of the largest upstream suppliers of mom-and-pop shops. When comparing our data with the census we observe 1.9 stores for every store that is present in the census (See Appendix Figure A.2). This gives us confidence that our data is broader than the census and includes all firms.

Apart from visibility to more firms, our data has two important advantages over what is available in the economic census. First, it includes the exact location (coordinates) of each shop. As shown in Figure 6 mom-and-pop shops are present in every municipality of the country, albeit differences in densities. And second, the data includes monthly information on total input purchases (the amount the m&p shop buys from the upstream supplier), which we use as a proxy for sales. Census data—while covering a wider range of variables—is only available every 5 years, making it impossible to study short-term effects of micro shocks.

Two issues that arise with the data is that we do not observe sales to final consumers and cannot observe total sales from all available products. The first concern is mitigated

by the fact that products from our supplier have relatively low shelf lives and representatives from the supplier exchange old products with new ones to guarantee freshness. This implies that input purchases from the mom-and-pop to the upstream supplier closely follow sales to the final consumer.¹⁸ As for the second concern, we make an implicit assumption that sales of other brands follow a similar pattern than those from our data. We think this is not an extreme assumption since sales from our supplier represent around 20% of total sales and include different brands and product types.

Because the data does not explicitly include a variable on opening and closing dates we create two different definitions of entry and exit and show that our results are robust to both. The first definition consists of simply using each ID as a distinct store, the first appearance as entry, and the last appearance as exit.¹⁹ With this definition a store can have periods of inactivity where we assume that no sales were made. Using this definition we have a total of 1,114,665 stores. The second definition assumes that if a store was not visited in the previous three months, the store has exited. If it appears again, then we consider it to be a new store. With this definition, we have 1,176,335 firms. Regardless of the definition we use, we observe high turnover of firms. In any given month there are around 790,000 mom-and-pop shops with an annual entry rate of around 16% and an exit rate of 14.7%.²⁰

Finally, our data also contains information on whether the shop has a tax ID, the gender of the store owner and the number of establishments each firm has. Table 1 shows summary statistics of our data. Some things worth pointing out is that mom-and-pop shops are mostly informal (83% of them don't have a tax ID), 62% are owned and operated by women and the vast majority of them are single-establishment firms. Mom-and-pop shops sell on average 223 dollars worth of products from our data-provider and each item costs around half a dollar.

¹⁸We do not worry about a store's ability to manage inventory and potential discrepancies that could arise because a store buys products that it cannot sell. This is because, the upstream supplier is the one responsible for keeping track of inventories. In every store visit, a representative from our partner company will look at all unsold products and exchange any that are close to their expiry date. Because representatives are paid according to their sales net of any exchanged products, there are strong incentives to ensure store owners are not overbuying products. Although frequency can vary from daily to biweekly depending on the store's size, it will always be automatically visited without any exerted effort from the store owner.

¹⁹For stores that are present in the first period we simply consider them as incumbent firms.

²⁰Our estimates are in line with entry and exit rates for informal and micro enterprises in developing countries (McCaig and Pavcnik, 2021). They are higher than rates for formal firms in developing countries and firms in developed countries. For example, using US manufacturing census data Dunne et al. (1988) find annual entry rates of 14% and exit rates of around 12%.

Household Expenditure. To look at household's expenditure patterns we use Mexico's household income and expenditure survey (ENIGH). This survey is publicly available from Mexico's National Statistical Institute (INEGI). Because the deregulation of gas prices happened in the last quarter of 2017, we use three waves of the survey: 2016, 2018, and 2020, which contain information on close to 100 thousand households. The survey includes comprehensive income and expenditure data; importantly, because people report in a diary what and where they buy, we can see the type of store where each good was purchased. That way, we are able to see consumption both at mom-and-pop shop as well as in modern supermarkets to understand substitution patterns.

Prices. In order to look at changes to prices following the gas price shock we use confidential price data used by INEGI to construct Mexico's consumer price index (CPI). Every week, INEGI's enumerators obtain price quotes at the brand, pack-size and variety level (for example, diet soda Coca-Cola 600ml bottle) for a number of products at different establishments. Importantly, the confidential data includes information on the municipality where the price was recorded and the type of establishment (i.e. traditional or modern). This is relevant because we can see generalized price changes as well heterogeneity by traditional and modern stores following our municipality level shock. The final data contains 2.7 million store-price observations over the period 2016-2020.

Gasoline price. To measure gas price changes we obtained daily data of prices at the gas-pump at every gas station in the country. As part of the Energy Reform, every gas station is mandated to report their prices every day and the data is published daily by Mexico's energy regulatory commission CRE with information on the name of the gas station, the address, the type of fuel (gasoline or diesel), the type of grade based on octane level and the price reported. Because no publicly available panel exists, we obtained confidential data through Petro Intelligence, a marketing research firm in the gasoline and transportation sector in Mexico. Our data also contains coordinate-level information on the location of each gas station. Because our analysis is at the municipality level, we create quarterly averages of the price in each municipality. Our data covers the period from 2017-2020.

Gasoline distribution centers. In order to instrument for the rise in gas prices, we use a municipality-level measure of distance to the nearest distribution center. To construct the distance measure we use INEGI's establishment directory DENUE to locate all the ports, refineries and border entry points where gasoline is shipped from. In total there

28 different distribution centers across the country. For municipalities with gas stations (64.9%), we compute the distance from every gas station to its nearest distribution center and average over all them. For municipalities with no gas station (35.1%), we first compute the distance from the municipality's centroid to the closest gas station and then add the distance from that gas station to the closest distribution center.

Population census. We complement our data using the 2010 population census to create controls for all of our regressions.

5 Identification

We want to study whether and how market structure is affected when consumer transport costs change. Increasing transport costs modifies how mobile people are and how much they are willing to move in order to shop. This in turn can have effects on which firms enter (or exit) the market and on their size. We take advantage of the deregulation of the gasoline market in the last quarter of 2017, and use it as an exogenous shock that increased consumer transport costs. As part of the Energy Reform, Mexico moved away from a national subsidized price of gas to one determined by the market. Although people anticipated the shock, we argue that the variation across municipalities was exogenous and not foreseen by store-owners, suppliers or consumers. We thus compare municipalities where gas prices increased to municipalities that suffered less of price hike, before and after the shock.

To ease endogeneity concerns stemming from the fact that gas prices might be correlated with changes in local economic conditions which would in turn affect market structure, we instrument gas prices. We do it by using the distance from each municipality to the nearest gasoline distribution center. The idea being that once prices were able to fluctuate, municipalities with higher logistics cost experienced a larger increase in gas prices relative to municipalities closer to distribution centers.

To construct our instrument we first identify the different distribution centers in the country which are composed of refineries, ports and entry points at the Mexico-US border. In total, there are 28 distribution centers and we obtain their location using INEGI's establishment registry DENUE and measure the linear distance from every gas station to the closest gasoline distribution center. For each municipality, we average over all gasoline station distances. In the Appendix, Figure A.8 shows a map of the instrument, depicting the distances from every municipality to its closest distribution center.

First stage. We use the distance measure in the following first stage specification:

$$\log(gasPrice_{mt}) = \alpha_m + \delta_t + \beta \log(distDistrCntr_m) \times Post_t + \Gamma X_{m0} + \epsilon_{mt} \quad (3)$$

where m represents a municipality and t represents a quarter. We include municipality and time fixed effects and X_{m0} are a set of baseline municipality-level control variables. Our coefficient of interest is β which captures the effect of being further away from a distribution center on gasoline prices post deregulation.

Reduced form. We then turn to reduced form event-studies of the form:

$$Y_{mt} = \alpha_m + \delta_t + \sum_k \beta_k (\log(distDistrCntr)_m \times \mathbb{1}[t = k]) + \gamma_0 X_{m0} + \epsilon_{mt} \quad (4)$$

where m represents a municipality and t represents a quarter. For all specifications we include municipality and time fixed effects, cluster standard errors at the municipality level and include municipality-level controls of baseline characteristics. Our coefficient of interest is β_k which captures the reduced form effect of being further away from gasoline distribution centers at different points in time.

IV specification. Because deregulation happened in a somewhat staggered fashion with a minority of states and one municipality deregulating prices before everyone else, we exclude them from the analysis. Our final data contains 2,333 municipalities in 29 states. Our main equation of interest is the following second stage equation:

$$Y_{mt} = \alpha_m + \delta_t + \widehat{\beta}(\widehat{\log(gasPrice}_{mt}) \times Post_t) + \gamma_0 X_{m0} + \epsilon_{mt} \quad (5)$$

where we instrument $\widehat{gasPrice}_{mt}$ with equation 3.

We revisit the identifying assumptions we are marking in our estimation strategy. To start, our identification strategy must satisfy the two main IV assumptions. Relevance requires that municipalities that are further away from gasoline distribution centers experience larger gas price increases, which we can assess directly from the first stage regression. For the exclusion restriction to hold we require that distance to distribution centers only impact market structure via changes in consumer transport costs. One might

worry that being far away from a distribution center is correlated with other characteristics that impact market structure. These concerns are alleviated by two facts. First, for all of our results we look at the reduced-form event-study graphs and find no pre-trends. Second, we add a set of municipality level controls that include population counts, a remoteness measure that takes into account how many people in a municipality are disconnected from a main road, the share of households with cars and average income to all our specifications and don't see relevant changes in our point estimates.

Finally, we recognize that the location of distribution centers was unlikely to happen randomly, but it is hard to imagine their placement has anything to do with our outcomes. Distribution centers constitute large projects that were built many years ago and include ports, refineries and customs between the US-Mexico border (for example, the last refinery to have been built was in 1979). The Energy Reform did not induce entry or exit of any gasoline distribution center.

6 Results

In this section we present empirical results. In Section 6.1 we begin by showing a strong first stage which ensures we have enough power for using our instrument. In Section 6.2 we present our main results which look at how transport costs affect market structure. In Section 6.3 we zoom into the firms that are entering the market and characterize the selection effect. Next, in Section 6.4 we provide evidence in support of our mechanism. That is, we show that household's mobility is in fact affected by the gasoline shock and shopping patterns change. Last, in Section 6.5 we go through different robustness checks of other potential confounding factors that could be occurring and find no evidence in support of them.

6.1 First Stage

We start by documenting the first stage relationship: do municipalities that are further away from gasoline distribution centers experience higher gas price increases after the policy? We expect this to be the case as longer distances to distribution centers mean a higher logistics cost which was not reflected in the price before. Figure 7 shows the first stage results of regressing the logarithm of the distance to a distribution center on the logarithm of gasoline prices. We plot the coefficients for two periods before the policy change and ten periods after, where each period represents a quarter. Gas prices in the periods before deregulation took place did not differentially affect gas prices (confirming

that gas stations did not deviate from the date the policy came into effect), while prices in the post-deregulation period increased persistently. Controlling for baseline characteristics, such as: share of cars in the municipality, remoteness as measured by the percentage of people without access to a main road, income level and population does not modify the coefficients as shown in Appendix Figure A.9 which shows regression coefficients with and without controls.

In Table 2, focusing on Panel A which includes the full sample, Column 1 shows the coefficient from running Equation 3 which establishes the first stage. A 10% increase in distance implies a .06% increase in the price. To interpret the magnitude, Figure 8 plots distance to the nearest distribution center against the predicted values of gas price changes before and after deregulation. Municipalities that are furthest from distribution centers experience gas price hikes almost 5% larger than municipalities closest to distribution centers. The strong first stage (F-stat value of 112) gives us enough power to use distance to gasoline distribution centers as our instrument.

6.2 Market structure: number and size of firms

Our mom-and-pop shop panel contains data from 2017 to 2020, which we restrict to the first quarter of 2020 to avoid the period of the beginning of the COVID-19 pandemic, where mobility was largely impacted and the service sector severely restricted. Turning to outcomes, we begin by showing reduced form effects of being further away from gasoline distribution centers. In particular, we ask: how does distance to distribution centers impact the number of available mom-and-pop shops and their size. Figure 9 shows the event-study reduced form effect on number of stores in a municipality. We see that before the deregulation went into effect, there were no systematic differences between municipalities. Once the policy change happened, there was a relative increase in the number of stores in treated municipalities. The effect started out slowly but picked up one year after the opening of the market. The delay in openings (relative to the moment gas prices increased) is likely due to prospective store-owners having to adapt a space and establish contact with upstream suppliers to stock their store before they could officially open. It might also be explained by a delay in consumers responses on where to shop.

For the magnitude of the effect of increased number of stores we focus on the IV estimates. Table 2 column 2 reports the effect of the gas price increase. The effects are large in magnitude, a 1% increase in gas prices results in a 4.8% increase in the number of stores. That translates into 21 more stores in a municipality.

To further understand what is driving the increase of stores, we look at entries and ex-

its. Our model predicts that following an increase in consumer transport costs, new stores enter to satisfy the new fragmented markets. This implies that empirically, we should expect the results to be driven primarily by increases in entries and not by decreases in exits. Table 3 shows the corresponding IV estimates. Because there are municipality-quarter pairs that do not experience any movement in the number of stores, we use the inverse hyperbolic sine to transform our variables and avoid log transformations that are not defined at zero. We see that in fact, entry is explaining our results. There is an 13.5% increase in entry and, while exit is also decreasing, the coefficient is much smaller (-0.73) and not significant.

Next we turn to effects on aggregate sales at mom-and-pop shops. As we discussed in Section 3 where we introduced the model, there are two ways in which an increase in gas prices affects mom-and-pop shops: (1) through a substitution channel by increasing the cost of going to the supermarket and (2) by increasing transport costs in general and reducing mobility across the city. If the first effect dominates we would expect to see an important increase in aggregate sales at mom-and-pop shops, if in the other hand the second effect dominates, demand at mom-and-pop shops would not increase since people would simply be switching where they shop but not the type of store.

Figure 10 shows the reduced form quarter-by-quarter coefficients of aggregate sales at mom-and-pop shops. After the gasoline market opens, there is a slight drop in aggregate sales in affected municipalities the first three quarters after the shock but the effect dissipates and appears to reverse after that. The IV estimate (Table 2 column 4) implies that a 1% increase in the price of gasoline increases average sales by 1.6% or a 3,975 dollar increase in total sales. While the effect is positive the coefficient is not significant.

If the only mechanism operating was substitution away from supermarkets and into mom-and-pop shops, aggregate sales would unambiguously increase. Because that is not what we observe in the data, we interpret the large standard errors as an indication of both mechanisms operating. In some areas demand is increasing because there is in fact substitution away from supermarkets but in other areas demand is staying flat with a change only on the specific store where people are purchasing their goods. In this sense, the model gives us a specific micro-prediction which we can test. Aggregate sales at mom-and-pop shops should follow an inverse U shape effect with respect to distance to the closest supermarket.

We can test the prediction of an inverse U-shaped effect across space with respect to distance from a municipality to the nearest supermarket. To that end, we identify the location of all supermarkets in the country pre-deregulation using the national registry of firms (DENUE) and calculate the distance from a municipality's centroid to the closest su-

permarket. The first three columns of Table 4 shows the effect on (m&p shops) aggregate sales at different terciles of distance. The largest effect is concentrated in the second tercile (T2) as the model predicted. For people who are close to a supermarket (T1) the gas price shock does not affect them very much as they only have to travel on average 5 kilometers to reach a supermarket. For those far away from a supermarket there is no substitution effect since most likely nobody was going to a supermarket anyways (on average they would have to drive 40 km to reach one).

As for the effect on number of stores we see a similar pattern although we cannot confirm that the coefficients are significantly different (Columns 4-6 of Table 4). The fact that we see a significant and large increase in the number of stores both for the first tercile and the last tercile are indicative that the mechanism behind our results are not completely driven by a substitution effect from supermarkets to mom-and-pop shops. Panel b of Table 2 confirms as well that the same patterns that we observe using the full sample are present when we restrict to only municipalities without a supermarket. We provide further evidence for both mechanisms operating when we look at outcomes using household expenditure survey.

Our third outcome on market structure looks at what happens to the average size of a firm (as measured by average sales) in places that are further away from distribution centers relative to those closer. Figure 11(a) shows the reduced form quarter-by-quarter coefficients of equation 4 on average sales. We observe a reduction in the size of firms in treated relative to control municipalities. For the magnitude of the effect we use the IV estimates (Table 2 column 3) which imply that a 1% increase in the price of gas decreases sales by 3.3% or by close to 15 USD. Note that the sales we are able to see are only a fraction of total sales. If we assume that sales for other brands and goods follow a similar pattern and that our data provider represents around one fifth of all sales, then sales decrease by \$75 USD in each store.

To understand whether stores entering are stealing business from incumbents or whether entrants are very small and so mechanically pushing average size down, we look at average sales restricting our sample to only include firms that were operating in the first quarter of 2017 (i.e. first period available in our data). If entering firms fully explain the drop in average size then we would expect no change in size for incumbent firms. Figure 11(b) plots the coefficients of the reduced form effects for both the full and the restricted sample. We see that incumbents average sales closely mimic the drop in size as when using the full sample, their drop is 75% the size of the total drop in average sales. In this sense, the decline in average sales is explained by large business stealing effects.

As a final exercise in understanding market structure effects we look at heterogeneity

ity by the number of mom-and-pop shops that exist in the pre-period. We expect both the number of stores and the business stealing effect to be mediated by the number of incumbents. In other words, places that start out with less mom-and-pop shops should see larger effects in average sales than those where more stores exist at baseline. We also expect less shops to enter in municipalities with thick markets. In order to test this, we run the same IV specification as equation 5 and add an interaction term in the following way:

$$Y_{mt} = \alpha_m + \delta_t + \beta(\widehat{\log(gasPrice}_{mt}) \times Post_t) + \sum_q \rho_q (M&P \mathbb{1}(quintile = q)_m \times \widehat{\log(gasPrice}_{mt}) \times Post_t) + \gamma_0 X_{m0} + \epsilon_{mt} \quad (6)$$

The coefficients of interest are ρ_q which indicate how the outcome variable is impacted in municipalities on different quintiles of the baseline mom-and-pop shop distribution. In Table 5 we show the results by quintile. A clear pattern emerges: as markets become thicker less stores enter and the business stealing effect becomes smaller. These results imply that the effects are mostly concentrated in municipalities with less shops at baseline.

6.3 Selection of stores: quality and fixed costs

Our model predicts that as transport costs increase, people want to shop locally and quality becomes less relevant. Additionally, because demand is more fragmented the mom-and-pop shops that are able to enter the market are those with low fixed cost of entry since. This is because only these shops find it profitable to operate even with few consumers. These two facts taken together have an implication for the type of stores that enter the market. We would expect them to be lower quality and have low fixed costs of entry.

Quality To empirically look at how average quality changed after the shock to transport costs we need a firm-level quality measure. While our data does not include additional information that can be used to measure quality, we can take advantage of the panel nature of the data and obtain a firm level quality measure by running the following regression:

$$sales_{jtl} = \phi_{AgeBin_j} + \alpha_{tl} + \gamma_j + \epsilon \quad (7)$$

where j a store, t represents a quarter and l represents a locality. In this regression, α_{tl} is a quarter-by-locality fixed effect and it captures all demand shocks to the firm.²¹ ϕ_{AgeBin} is the coefficient on the discretized value of the age of a firm and controls for the fact that older stores might also have more sales than newer stores. γ_j captures the remaining mom-and-pop shop level variation. Because markups are fixed and there is very little variation in prices, we interpret these coefficients as all the non-price productivity differences between firms, this could be hours of operation, cleanliness or costumer service for example. We use the coefficients to construct a municipality-quarter level quality value, where variation is coming from the change in composition of operating firms within a municipality.

Figure 12 plots the quarter-by-quarter coefficients of regression 4 where the outcome is the average value of operating firms quality (coefficients γ_j from Equation 7). We see a decrease in the average quality of firms in treated relative to control municipalities. Doubling the distance from a gasoline distribution center decreases quality of firms by around .2 standard deviations. To ensure the effect is not mechanical, we check to see whether quality is static overtime or something that store-owners can learn and improve upon. We use pre-treatment data and look at the correlation between quality (as measured by γ_j) and a firms' age. If quality changed overtime then we would expect older firm to have higher quality than younger ones. Figure A.10 shows that this is not the case. Instead, we see a flat relationship between the two variables.

Fixed cost of entry To evaluate whether entering mom-and-pop shops had lower fixed costs of entry in treatment relative to control municipalities we use pre-2017 real estate prices. Although most people open a shop in their own property we think of this fixed cost as the opportunity cost of forgone rents the shop owner could be collecting if they used the space for something else.²² In this sense, real estate values are a good proxy for rents. Because of data limitations we are only able to do the exercise for Mexico City where we have access to prices at the locality level (equivalent to a census tract).

We use Mexico City data from the period before deregulation to construct a municipality level measure of how much is being paid in fixed cost of entry. Similar to our quality measure, the variation in this measure comes from the fact that mom-and-pop shops in different localities exist every period. Our measure captures whether entrants in

²¹A locality is equivalent to a US census tract, so the fixed effect captures very localized characteristics like the number of other stores that exist in that quarter and the number of consumers.

²²Another alternative is to use wages as fixed cost of entry to reflect their outside option which is working for a wage. For this exercise, wages are not possible to use because we don't have granular level data, so there is no variation in wages.

places that are further away from distribution centers pay less fixed cost of entry than entrants in places close to distribution centers. Figure 13 plots the coefficients of the reduced form. Note that after the shock entrants in municipalities that are further away entered in “cheaper areas”. Doubling the distance from a gasoline distribution center decreases average fixed cost of entry by around half a standard deviation.

6.4 Mechanisms through which gas prices affect market structure

In the previous section we argued that when gas prices increase, market structure is affected through two mechanisms: a substitution channel across sectors (less people visiting supermarkets and opting for mom-and-pop shops) and a fragmentation channel within mom-and-pop shops (changing where people buy). Here we provide further evidence of both effects being present.

Substitution away from supermarkets We are interested in knowing whether households changed their shopping behavior across types of stores. In other words, as gas prices increased did people substitute away from supermarkets and into mom-and-pop shops? In order to answer this question we use data from INEGI’s Household Income and Expenditure Survey (ENIGH). The survey is a cross section run every two years and in it they ask households to log how much they spent and at which type of store. We use three waves of the survey: 2016, 2018 and 2020 to see how the gas price shock affected where people buy. Our final data covers 1,460 municipalities and over 200,000 households. Because we only have three periods we cannot run event-studies but we can directly estimate a modified version of equation 5.

$$Y_{h(m)t} = \alpha_m + \delta_t + \beta(\widehat{\log(gasPrice}_{mt}) \times Post_t) + \gamma_0 X_{m0} + \eta_h C_h + \epsilon_{h(m)t} \quad (8)$$

where h represents a household in municipality m and t represents the wave year of the survey. We use the same instrument for $\widehat{\log(gasPrice}_{mt}$ as we did in the main regressions, distance to the nearest distribution center. X_{m0} is a vector of baseline number of supermarkets and mom-and-pop shop at the municipality level. We also include controls for household characteristics C_h . Table 6 reports results for whether people report buying at mom-and-pop shops or at supermarkets (Columns 1 and 2), how frequently they shop for groceries (Column 3 and 4), and how much they spend at each type of store (Column 5 and 6) in places where gas prices

Being exposed to a higher gas price after deregulation via being further away from a gasoline distribution center leads to a decrease in the likelihood of shopping at supermarkets and a slight increase in the likelihood of buying at mom-and-pop shops. While coefficients are not significant, the signs of the effects are as expected. The modest increase in households reporting that they are buying at a mom-and-pop shop is likely due to the fact that already most people report buying at least one item at this stores, as reflected by the baseline mean of 91%.

A different measure of where households are buying their groceries is the frequency with which they visit a store. The survey directly asks households how frequently they go grocery shopping. The possible answers are daily, biweekly, weekly, every two weeks or monthly. We group this answers into high frequency shopping (daily and biweekly) and low frequency shopping (weekly, every two weeks and monthly) and report coefficients in Column 3 and 4 of Table 6. A similar pattern emerges, more households report buying at high frequencies suggesting that more shopping is happening at mom-and-pop shops. And less households report buying at low frequencies implying that they visit supermarkets less frequently.

Lastly we look at expenditure at both types of stores (Columns 5 and 6 of Table 6) and see a similarly large decrease in how much households are spending. For a 1% gas price increase households spend 0.5% less in mom-and-pop shops and 0.4% less in supermarkets.

Substitution within mom-and-pop shops The mechanism behind gas prices affecting substitution within mom-and-pop shop is through how people commute within a city. To look at whether gas prices changing actually modified household's behavior on how they commute we again utilize data from INEGI's Income and Expenditure Survey and look at gasoline and public transportation usage and expenditure. We estimate Equation 8 and report coefficients in Table 7. The outcome variables in the first two columns are dummies that take value of 1 if the household reported expenditure in that category (Column 1 reports result for gasoline and Column 2 for public transportation) and 0 otherwise. For a 1% in gasoline there is a 0.23 percentage point decrease in households purchasing any gas and a 0.48 percentage point increase in households using public transportation.

Looking at intensive margin results (Columns 3 and 4), for those purchasing gasoline there is a 0.96% decrease in the liters reported and a 0.94% increase in public transportation expenditure. These results are large in magnitude and suggest that people are extremely sensitive to gas price changes.

With ideal data the next exercise would be to see how gas price increases affect which

mom-and-pop shop households shop at. We expect that following the gas price shock, households switch to shops closer to them. While no such data exists we can overcome this data challenge thanks to the granularity of our data. Within each municipality we uniformly sample 1,000 random points and compute the distance between each point to its closest store, for every quarter. With that, we construct a municipality-quarter average time traveled measure to capture how far away people are from the closest shop. In other words, we obtain a consumer market access measure for each municipality in terms of distance. To make things concrete, Figure A.11 shows a graphical example of a municipality with sampled points in grey, incumbents in blue and entrants in red. We calculate the distance from every grey point (which represents a potential household) to the closest store in each quarter. The magnitude of the change in consumer market access tells us something about where stores are opening. If new mom-and-pop shops open in places far enough from other incumbents then it implies that new markets are now being covered.

Figure 14 shows coefficients from Equation 4 where we see a decrease in average distance traveled. The results imply that new stores aren't simply opening in the same places as old stores are located. This was an important concern, because mom-and-pop shops tend to agglomerate into the same street. IV estimates shown in Table 7 Column 5 tell us the magnitude of the effect. A 1% increase in gas prices, average distance traveled decreased by 1.87% or by close to 90 meters. If we consider the 5% increase in gas prices in municipalities furthest away from distribution centers, this implies that distance traveled was reduced by 450 meters. Two things are worth pointing out. First, this is a lower bound as the distance measure is constructed using linear distance from each point to the closest store. Second, a reduction of 450 meters implies that people walk close to a kilometer less to and from the shop.

6.5 Robustness

Real wages An alternative mechanism that could explain our results are real wages falling in places where gas prices go up. As households face a reduction in income they have a bigger incentive to open a mom-and-pop shop as a side business to complement their income. Descriptively, the idea of opening a mom-and-pop shop to supplement income seems unlikely since 92% of owners report operating the shop as their main business and close to 85% of shops report being owner-operated (ENAPROCE 2022).

Empirically, we can test this mechanism by looking at the evolution of wages and prices separately to determine whether real wages changed. To explore this possibility we begin by using the microdata on prices that INEGI uses to construct the consumer

price index. A nice feature of the price data is that it not only tracks prices of goods but also of services like health, education and rents. The confidential data includes the municipality where the price was recorded which we use to verify that prices did not change differentially after the gas price shock.

To test for prices effects, we estimate a variant of equation 4 using product-by-store level price data. We follow the same specification that [Atkin et al. \(2018\)](#) and [Higgins \(2018\)](#) use:

$$\log(price)_{gst} = \eta_{gs} + \delta_t + \sum_k \phi_k Treated_{m(s)t}^k + \epsilon_{gst} \quad (9)$$

where g is a barcode-equivalent product, s is the store where the price was recorded and t is a quarter. We average the price data to the quarter level, to coincide with the time periods we use for our main analysis. We include product-by-store fixed effects as well as quarter fixed effects. Figure 15(a) shows that all coefficients are statistically insignificant both before and after the gas price shock.

Next, we turn to look at wage effects using publicly available social security data. Figure 15(b) shows reduced form coefficients of Equation 4 using log wages as our outcome. Again we see no systematic wage declines in areas that are further away from gasoline distribution centers and hence had a greater gas price increase. These two figures taken together rule out real wage effects as the mechanism behind our results.

Employment A second mechanism that could explain our results is employment opportunities changing. It could be the case that firms cannot adjust on the wage margin but instead adjust on total employment. If unemployment level increases in areas where gas prices increase, then the increase in number of mom-and-pop shops could be explained by worse outside options.

To look at employment changes we again use publicly available social security data which tracks all employment in the formal sector. Figure 16 shows reduced form coefficients for the evolution of employment. There is no decline in employment. In the contrary, there appears to be a non significant and small increase effect in employment for municipalities that are further away from gas distribution centers. This result suggests that employment changes are not driving the increase in mom-and-pop shops.

Prices A third potential mechanism is that relative prices across store formats are changing. For example, one could theorize that supermarkets are better at changing prices so

that after the gas price shock they increased the price of their goods. This in turn could make (price sensitive) consumers switch their shopping location.

To empirically test this, we again use INEGI's price data and estimate Equation 9 separately for modern stores (i.e. supermarkets) and traditional stores exploiting the fact that enumerators report the type of store where the price was recorded. Figure 17(a) shows the evolution of prices in modern stores and Figure 17(b) in traditional store. For both type of stores we see no price changes, ruling out that prices are the driver of substitution patterns.

Upstream supplier An implicit assumption we have been making is that the change in gas prices primarily affected consumer transport costs and did not affect suppliers (mom-and-pop shops and their upstream suppliers). We discuss this assumption in more detail.

As we laid out in Section 2, the institutional setting alleviates our concern that mom-and-pop shops were severely impacted by gas price increases since most of the products they sell are delivered straight to their door. Surveys conducted by INEGI reveal that less than 5% of expenses correspond to gasoline. Upstream suppliers in the other hand, could have been affected by increases in gas price. But even if this is the case, we would expect the sign of the results to go in the opposite direction. That is, if upstream suppliers want to reduce their gasoline expenditure due to increasing prices, we would expect to see less store entry (not more). Especially as it appears that the size of the market is not growing (as measured by aggregate sales).

7 Parameter estimation

This section describes the structural estimation of the model's parameters. We begin by laying out the data we use and the selection rule to ensure an equilibrium. In Section 7.2 we estimate the elasticity with respect to transport costs (θ) which is informative of local spillovers once new firms enter. In Section 7.3 we estimate the parameters of the joint distribution of quality and fixed costs of entry ($\mu_F, \mu_\gamma, \sigma_F, \sigma_\gamma$ and $\rho_{F,\gamma}$).

7.1 Data and equilibrium

For our estimation exercise, we exploit the granularity of our data to look at within city effects and focus solely on Mexico City for computational reasons. The primary geographic unit used in the analysis is a census tract (Área Geoestadística Básica). The city is partitioned into 2,432 tract that are contained within 16 municipalities.

Population data comes from INEGI's 2010 population census. This provides the residential population of each block. Data on quality comes from the coefficients on the fixed effects of the regression described in Section 6. For fixed cost of entry we use the monthly average income at the tract level which we obtain from INEGI's Income and Expenditure Survey (ENIGH). Given that the physical cost of opening a store is low provided our context, we use this definition of fixed cost to reflect the opportunity cost households incur in when opening a mom and pop shop.

Travel times are calculated using linear distances from and to each census tract centroid and converted into walking times using a calibration exercise that uses random trips in google maps. Following the urban economics literature (Ahlfeldt et al., 2015; Tsivaniidis, 2019; Zárate, 2019) we parametrize commuting costs using the following expression:

$$\tau_{ij} = \exp(\delta_\tau \text{time}_{ij})$$

where time_{ij} is the average travel time in minutes of going from location i to location j . We take $\delta_\tau = 0.013$ from Zárate (2019) who uses data from Mexico City to compute it in order to transform travel times into costs.

Lastly we set the markup to be 20% of total sales in accordance to reports from ANPEC (National Alliance of Small Businesses) on how much these stores earn.

Equilibrium. Having a discrete-entry model is challenging due to the discrete jumps we get every time a store opens (or closes). Although we cannot guarantee the uniqueness of the equilibrium we are able to write an algorithm that finds an equilibrium for different urban configurations.²³ Importantly, our algorithm uses the smallest possible granularity by either opening or closing a firm one-by-one and checking whether we have reached an equilibrium (that is, all opened stores have positive profits, and all closed stores would have negative profits if they were to open).

Formally, let $\mathbf{y} = \{0, 1\}^N$ be an integer vector of size N (i.e. the number of blocks in the city), which indicates whether a firm in block j is opened or closed. Then, at every iteration the algorithm first evaluates if \mathbf{y} is at an equilibrium by calculating the profits of the firms that open and by computing the profits of each of the closed firms. To perform the last step, it opens each of the closed firms (one-by-one) and calculates the new profit distribution. If the opened firms have positive profits and the closed firms have negative profits, then the algorithm terminates and outputs \mathbf{y} . Otherwise, from all the closed firms

²³Other papers that deal with discrete-entry models use similar ways to find an equilibrium by having explicit selection rules. For example: Aguirregabiria and Vicentini (2016); Jia (2008); Matsuyama and Ushchev (2020).

with positive profits it takes the one with highest profits and opens it. Subsequently and considering this new opening, it calculates the profits for the opened firms. If any of these have negative profits, then it closes the one with the smallest values. At this point the algorithm has generated a new vector \mathbf{y} in which at most two changes from the previous vector may have occurred (an opening and a closing). The algorithm goes back to the evaluation step and iterates until it finds an equilibrium.

To be even more concrete, if we begin with an initial vector \mathbf{y} of only zeros, meaning that all firms are closed, then the selection rule is to first open the firm with the highest quality and continue iterating one firm at a time until we reach an equilibrium. Which equilibrium we are able to find depends on the initial \mathbf{y} vector.

7.2 Estimating θ

In this section we propose a method to estimate θ from the data. We begin by laying out the intuition using the model and then turn to our data to estimate it. This parameter is relevant as it tells us how sensitive people are to changes in transport costs and quality.

Estimating θ typically relies on detailed data of shopping behavior by consumers, which is hard to obtain in developing country contexts, even more so for the type of informal firms we study in this paper. To overcome this challenge, we propose a novel estimation strategy that uses indirect inference exploiting the spatially detailed high frequency nature of our data. We show that the geographic decay of the effect of entry by one firm on incumbent firms sales can be used to estimate this parameter.

To see the intuition from the model, suppose we start from an equilibrium in which the first $J' < J$ firms open: $\Omega \equiv \{1, \dots, J'\}$. This determines the profits of the firms that are currently operating in the market so that we can index profits of any operating profit by the set of other operating firms, this is

$$\begin{aligned}\pi_j(\Omega) &\geq 0 \quad j \in \{1, \dots, J'\} \\ \pi_{j'}(\Omega) &< 0 \quad j' \in \{J' + 1, \dots, J\}\end{aligned}$$

Now suppose that the firm in block $J' + 1$ obtains a random productivity shock such that it finds it profitable to enter the market so that market structure becomes $\Omega' \equiv \{1, \dots, J', J' + 1\}$. What is the effect on incumbents? For a given incumbent $j \in \Omega$:

$$\pi_j(\Omega') - \pi_j(\Omega) = -\mu \sum_i \underbrace{s_{ij}(\Omega)}_{\text{initial share } i \rightarrow j} \times \underbrace{s_{iJ+1}(\Omega')}_{\text{new share } i \rightarrow J+1} < 0$$

the decrease in profits for a firm in block j from the entry of a firm in block $J + 1$ is a weighted average across all blocks of the markup times the initial share of all sales that firm j obtained from consumers from i times the share that the new firm “steals” from the consumers in i . A firm will be more affected by the entry of another firm if the new firm “steals” a lot of consumers from the incumbent. The complete derivation is shown in Appendix B.1.

Crucially, the spatial decay of such business stealing effect depends on the magnitude of θ . To see this point, we simulate the effect of entry of a new store on incumbent stores depending on different values of θ . Appendix Figure A.12 shows the results, where we see that for higher values of θ only firms that are close to the entrant are affected, while firms further away don’t see a change in their revenue.

Leveraging our fine geographic panel data we can replicate a similar empirical exercise and match the decay in the data to the decay in the model to recover θ . In order to do this we take our full firm-level panel data and identify all entering firms.²⁴ The question we answer is: what happens to incumbents’ sales once a new firm enters. We construct various rings of 300 meters each around every store entry in order to measure the spatial decay.²⁵ We run an event study where event time is normalized to one period before entry and compare the effect of entry on incumbents’ sales. We interact event month dummies with multiple 300 meter rings and up to 1200 meters, indicating the distance from each incumbent store to the associated store entry (treated ring). Incumbents located between 900 and 1200 meters are the omitted group and serve as our control. We estimate the following event study equation at the incumbent shop j , entrant e and month t level:

$$\log(sales)_{jet} = \alpha_j t + \kappa_{e,r(j,e),m(j)} + \sum_{\tau=-6}^{15} \sum_{\rho} \beta_{\tau r} \mathbb{1}\{t = \tau\} \times \mathbb{1}\{r = \rho\} + \epsilon_{jet}$$

where j is an incumbent store in municipality m in month t and $r(j, e)$ is the ring r where j is located with respect to entrant e . $\beta_{\tau,r}$ is the coefficient of interest and it captures the evolution of sales of incumbent firms over time in each treated ring with respect to the outermost ring. The entry-date fixed effects ($\alpha_{e,t}$) flexibly account for time patterns across all rings around each store entry e . Entry-ring-municipality fixed effects ($\kappa_{e,r(j,e),m(j)}$) control for baseline differences of incumbents in each ring. Figure 18 shows the results.

²⁴Note that this exercise is independent from what we do in Section 5, here we are interested in looking at the effect of entry irregardless of the gas price shock.

²⁵As robustness we try with different sized rings and obtain that at the 300 meter mark, sales of incumbents stop being affected by a new mom and pop shop opening

When a new store enters, only the stores at a 300 meters distance have a decrease in sales, suggesting a fast spatial decay and thus a large θ . The fact that consumer's are so sensitive to transport costs and are willing to change where they shop even at small distances implies that a store's entry has important localized spillover effects that dissipate quickly with distance.

We can then take this empirical result and replicate the same exercise in the model to recover the value of θ . We obtain a value of $\theta = 11.2$. To benchmark this number, we look at the commuting elasticities obtained in [Zárate \(2019\)](#) for Mexico City and in [Tsivanidis \(2019\)](#) for Bogotá. In the case of Mexico City, elasticities are estimated to be 3.11 for workers in the formal sector and 4.66 for those in the informal sector. In the case of Bogotá, the commuting elasticity is 3.398. The fact that we get a much bigger number is not surprising. Not surprisingly our estimated elasticity is larger than in previous studies since our context is also different. Both papers references look at commuting elasticities for job choice while we explore a context where people are buying a non-differentiated product (same product-quality and same price).

7.3 Estimating the joint distribution of γ and F

We use the method of simulated moments to estimate the parameters underlying the relationship between γ and F . We assume that these variables come from a joint log normal distribution:

$$\begin{pmatrix} \log(\gamma) \\ \log(F) \end{pmatrix} \sim \mathcal{N} \left(\begin{pmatrix} \mu_\gamma \\ \mu_F \end{pmatrix}, \begin{pmatrix} \sigma_\gamma & \rho \\ \rho & \sigma_F \end{pmatrix} \right)$$

Given the observed equilibrium, we begin by obtaining estimates of the parameters: $(\hat{\mu}_\gamma, \hat{\mu}_F, \hat{\sigma}_\gamma, \hat{\sigma}_F, \hat{\rho})$. We obtain these moments directly from our data. For quality (γ), we use the fixed effect coefficients we obtained from Equation 7 in Section 6. For fixed costs of entry (F), we use Mexico City's wage information at the census tract level. The parameters obtained directly from these date, describe the mean and standard deviations of entering firms but not the underlying distribution of potential entrants. To remove this bias we estimate $(\mu_\gamma, \mu_F, \sigma_\gamma, \sigma_F, \rho)$ as follows:

1. Given the guess of parameters, we obtain many draws from a bivariate lognormal distribution
2. Given draws, we obtain a set of operating firms Ω according to the model

- Given surviving firms (entrants), we calculate the distance between the model moments and empirical moments, and minimize

8 The welfare effects of high transport costs

Using our framework in this section we quantify the effects of transport costs and fixed cost of entry in explaining the number of firms in the market. Then we discuss efficiency implications and do counterfactual analysis of taxing (or subsidizing) store entry.

Market structure under different levels of transport costs and fixed costs of entry We started out with the observation that Mexico and Indonesia have many more firms per capita than the US. The model and empirical exercise suggest that higher transport costs lead to more fragmented markets and thus more localized demand. It is this fact together with low entry costs that give us high density of stores with small sizes. As we've discussed before, the lack of regulation on these retail stores, the poor outside options for store-owners and the low investment they have to make to open a store all suggest that this fixed costs are low and lower than in a rich-country context.

To understand the magnitude of transport costs and fixed cost of entry in explaining the differences in market structure observed across Mexico and the US we take our baseline solution for the model using calibrated data from Mexico and run counterfactuals modifying transport costs, then modifying fixed cost of entry and finally modifying both at the same time. For our counterfactual exercise we use transport costs and fixed cost of entry as observed in the US. We take two different approaches in calibrating the difference in transport costs between the two countries and report both estimates and an additional estimate for the mid point. Table 8 shows our results, in the most conservative case, the number of stores observed would decrease by 7% if fixed costs of entry and transport costs in Mexico looked like those of the US. In the least conservative case we would see 41% less stores.

8.1 Welfare and efficiency

In order to think through welfare effects and efficiency we begin this section by deriving expressions for consumer surplus and producer surplus. We then use this expressions and our estimated model to look at the welfare consequences of subsidizing or taxing store entry.

Consumer welfare. Given an equilibrium market structure, Ω , the expected utility of consumers from i is given by:

$$\begin{aligned} CS_i &= \mathbb{E} \left[\max_j u_{ij} \right] \\ &= \Gamma [CMA_i(\Omega)]^{1/\theta} \end{aligned}$$

where $\Gamma \left(\frac{\theta-1}{\theta} \right)$ is a constant, and $CMA_i(\Omega)$ is the consumer market access for individuals from i and is defined as:

$$CMA_i(\Omega) \equiv \sum_{j' \in \Omega} \left(\gamma_j \tau_{ij'}^{-1} \right)^{\theta}$$

In order to get the expression for aggregate welfare, we can take the weighted average of consumer surplus and define $\lambda_i \equiv \frac{M_i}{\sum_j M_j}$ as the share of individuals that live in block i , such that:

$$CS(\Omega) = \Gamma \sum_i \lambda_i [CMA_i(\Omega)]^{1/\theta}$$

Observe that consumer welfare depends on market access which in turn is a function of both the number of stores (since that determines how far and how much people have to pay in transport costs) and the quality of stores.

Total welfare. Total welfare is simply given by the following expression:

$$W(\Omega) = CS(\Omega) + \sum_j (\pi_j(\Omega) - F_j)$$

where Ω is the set of operating firms. One important thing to note is that we exclude from our welfare calculation the profits of the supermarket. This is because, from a social perspective the planner does not care about the profits of supermarkets. The supermarket still plays a role in the sense that from the consumers side, the existence of the supermarket increases consumer market access. And from the producers side, how many people choose to go to the supermarket relative to the mom-and-pop shops will determine profits.

Is there excess entry? Ex-ante there is nothing in the model that tells us whether there is too much entry or not, but there is a trade-off every time a new store enters. Consumer surplus increases because there is love for variety (as defined by the number of stores in the market) while producer surplus decreases because of the business stealing effect. Which of these effects dominates depends on the parameters of the model.

To look at this more clearly we can look at the marginal effect on aggregate welfare of adding an extra store, i.e, going from a market structure Ω to Ω' :

$$\begin{aligned} W(\Omega') - W(\Omega) &= CS(\Omega') - CS(\Omega) + \sum_{j \in \Omega'} (\pi_j(\Omega')) - \sum_{j \in \Omega} (\pi_j(\Omega)) \\ &= CS(\Omega') - CS(\Omega) + \sum_{j \in \Omega} (\pi_j(\Omega') - \pi_j(\Omega)) + \pi_{J+1}(\Omega') \end{aligned}$$

In Appendix B.2 we show that plugging in values for consumer surplus and profits we get:

$$\begin{aligned} W(\Omega') - W(\Omega) &= \underbrace{\Gamma \sum_i \lambda_i \left\{ [CMA_i(\Omega')]^{1/\theta} - [CMA_i(\Omega)]^{1/\theta} \right\}}_{\Delta CS} \\ &\quad - \underbrace{\mu \sum_i \sum_j M_i s_{i,j+1}(\Omega') \left[s_{ij}(\Omega) - \frac{1}{\#\{\Omega\}} \right] - F_{J+1}}_{\text{Business Stealing}} \end{aligned}$$

The first term is the change in consumer market access which increases with one extra shop and the second term represents how much business the new firm is able to still from incumbents and the additional fixed cost that is paid.

Welfare effects of increasing fixed costs of entry In 2021, Mexico City decided to restart an old program that aims to regularize small establishments.²⁶ The program is specifically targeted to small stores and asks store owners to show a long list of documents (pictures of the outside and inside of the store, official ID, documentation of the space used as a store, payment for regularization, tax ID, etc.). We interpret this program as imposing a one-time cost which we can model as higher fixed costs of entry for all mom-and-pop shops. To calculate the increase in F we take the nominal cost that store-owners have to pay for the licence and scale it by the mean wage. We see this number as

²⁶More information on the program can be found [here](#).

the lower bound of the cost that is imposed by the program.²⁷

In Figure 19 we show the welfare effects of imposing higher costs of entry. Importantly we assume that the government is rebating back the tax to households. We compare welfare changes to the baseline case of no licensing costs. There are two relevant things to note from this figure. First, making mom-and-pop shops pay for a licence to operate decreases entry and increases welfare by 1.4% relative to the baseline case. Second, the baseline equilibrium (licensing cost = 0) is not far from the maximum welfare point. This is important because if the non-monetary costs of obtaining a license are high enough, then welfare would decrease.

Our results suggest that there is some scope for welfare gains by decreasing the number of stores in the market but not by much. We should point out that our results should be taken with caution since our model is restrictive in many ways: there is full information for both consumers and producers, entrants always have positive profits (since they know their type even before deciding to enter), and prices are fixed.

9 Conclusions

Developing countries are characterized by the prevalence of small firms. This paper established how transport costs and low fixed cost of entry can be important factors for understanding market structure. Using a novel confidential panel of firm-level data and a shock to consumer transport costs we provided micro-evidence of increases in transport costs resulting in more store entry and consequently, in smaller average sized stores (due to business stealing) and lower quality mom-and-pop shops.

We provided evidence for two mechanisms being at play for explaining these results using household level survey data. First, we document households substituting away from supermarkets and into mom-and-pop shops. And second, we see a meaningful decline in households consuming gasoline and a parallel increase in public transportation usage. This reduction in mobility within the city affected the choice of where people shopped and lead to substitution within mom-and-pop shops.

We then turned to the estimation of the relevant parameters of the model. We uncovered high elasticities with respect to transport costs, implying that markets are very localized and that there are strong business stealing effects from new stores entering.

The result from our welfare estimation implies there is scope for welfare increases by limiting the number of stores in the market. Nonetheless, even at the optimal licensing

²⁷This is because there are many other requirements to obtain the license like showing documentation that shop owners might not have and would need to pay an additional cost to obtain.

cost welfare could increase by 2% at most. This suggests that the observed equilibrium is not far away from the social optimum.

The results from this paper suggest that given the structure of demand, the number of firms we observe in the market is (close to being) efficient because of household's love for variety and high transport costs. This is informative to policymakers and researchers when designing supply interventions to bolster the growth of small firms. Alleviating supply side constraints will not necessarily result in fewer, larger, high-quality stores as long as demand is localized due to high transport costs.

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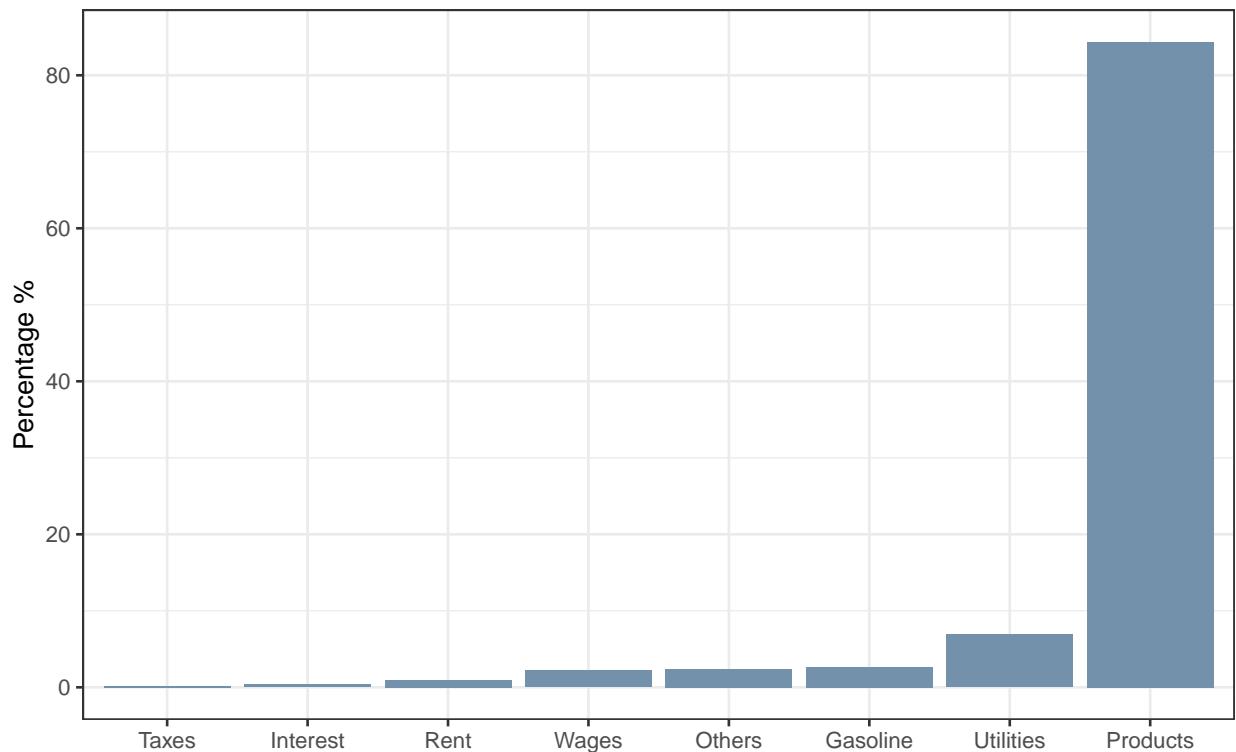
Figures

Figure 1: Typical medium-sized mom and pop shop



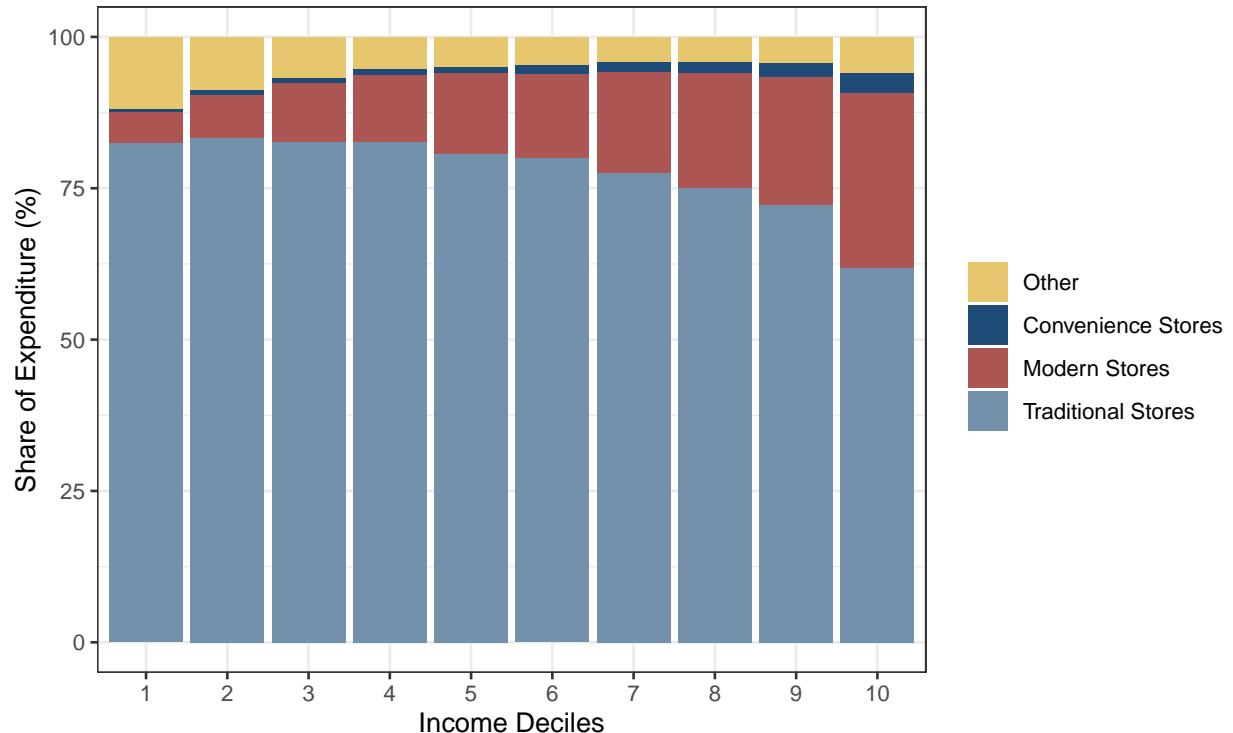
Notes: This figure was taken from google map's street view and shows a medium-sized mom-and-pop shop in Mexico City. As is typical of other stores, the store is part of a house (note the garage door on the left hand side). Another thing to note is that the majority of the infrastructure is from upstream suppliers (the posters, the fridge and even the store awning). ([back](#))

Figure 2: Expenses of mom-and-pop shops



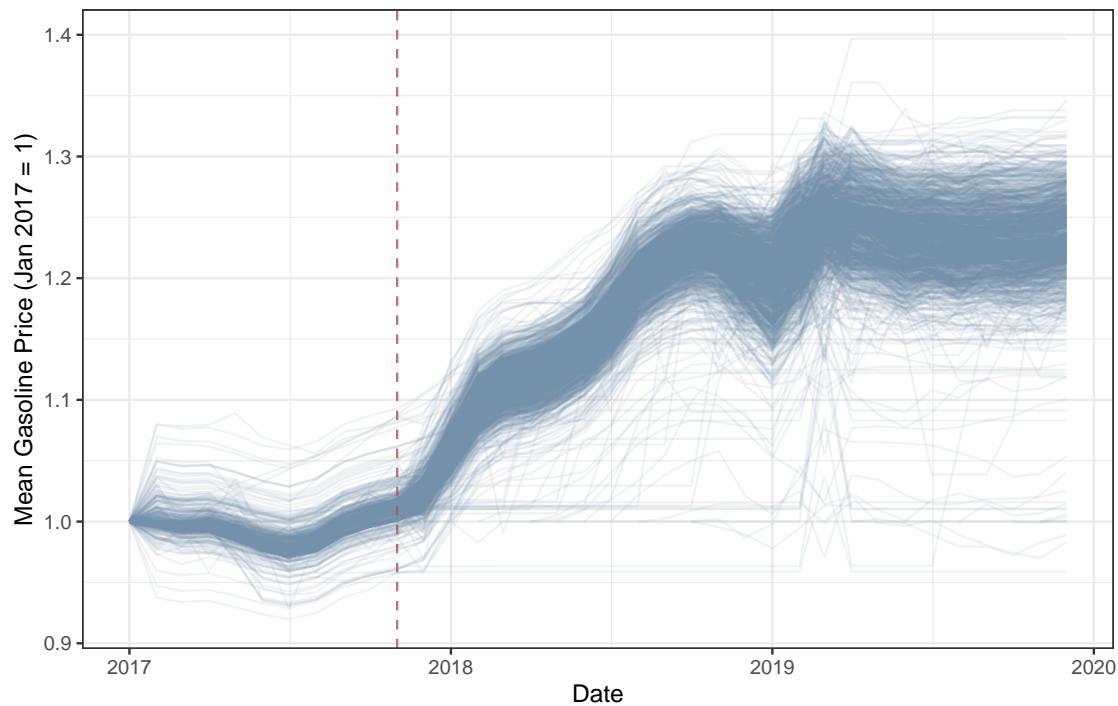
Notes: This figure uses data from INEGI's 2020 Income and Expenditure Survey ENIGH where they ask business owners how much they spend on different expenses. We filter the data to only include mom-and-pop shop owners, $N = 10,918$. Over 80% of expenses correspond to buying products to resell. ([back](#))

Figure 3: Food Expenditure by decile



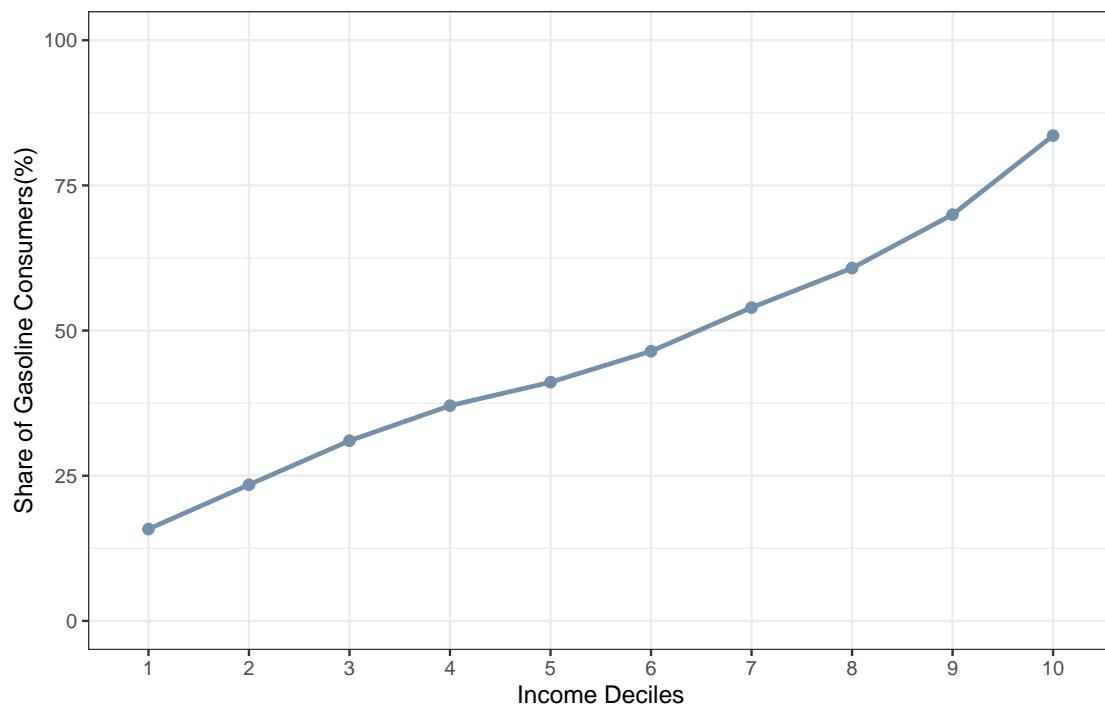
Notes: This figure uses data from INEGI's 2018 Income and Expenditure Survey ENIGH. The survey asks households where they purchase their food and household goods. Traditional stores include mom-and-pop shops (57%), street vendors (22%), and speciality shops (21%, which includes tortilla-shops, meat-shops, etc). [\(back\)](#)

Figure 4: Raw trend of gasoline prices at municipality level



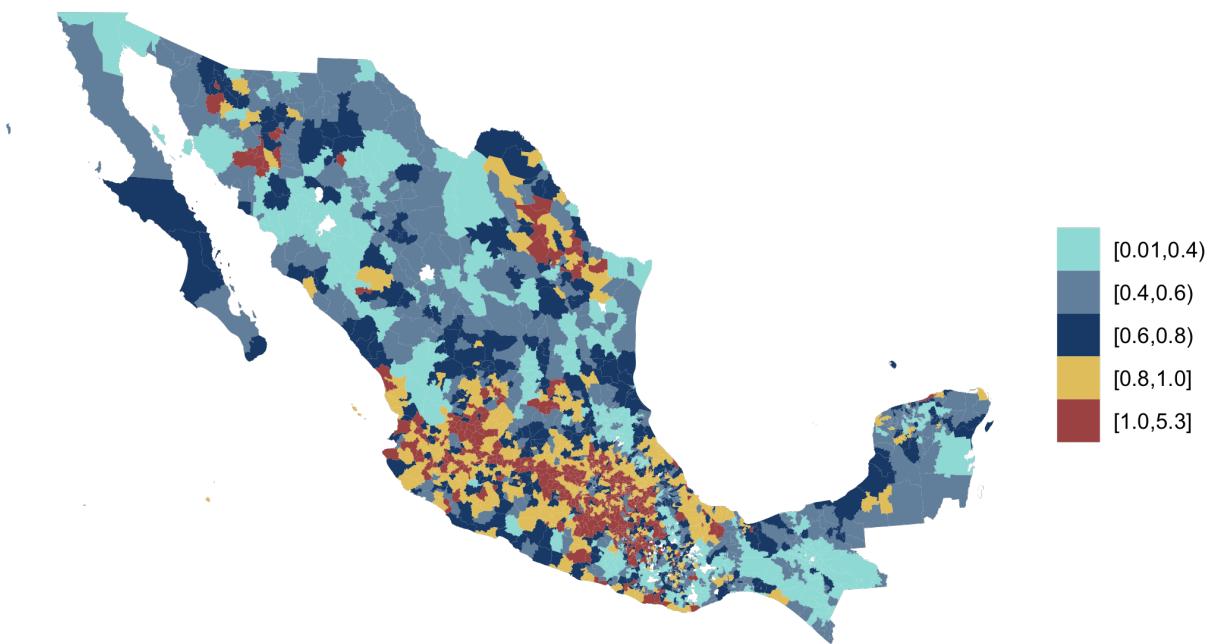
Notes: This figure shows the raw trend of gasoline prices. Each line represents a municipality. Prices are normalized to January 2017 prices. The red dotted line represents the date prices where allowed to fluctuate. Data employed is daily gas pump-level information obtained from PetroIntelligence. As part of the Energy Reform, gas stations were mandated to report their daily price and the market regulator posts it online ([back](#))

Figure 5: Gasoline Expenditure by income decile



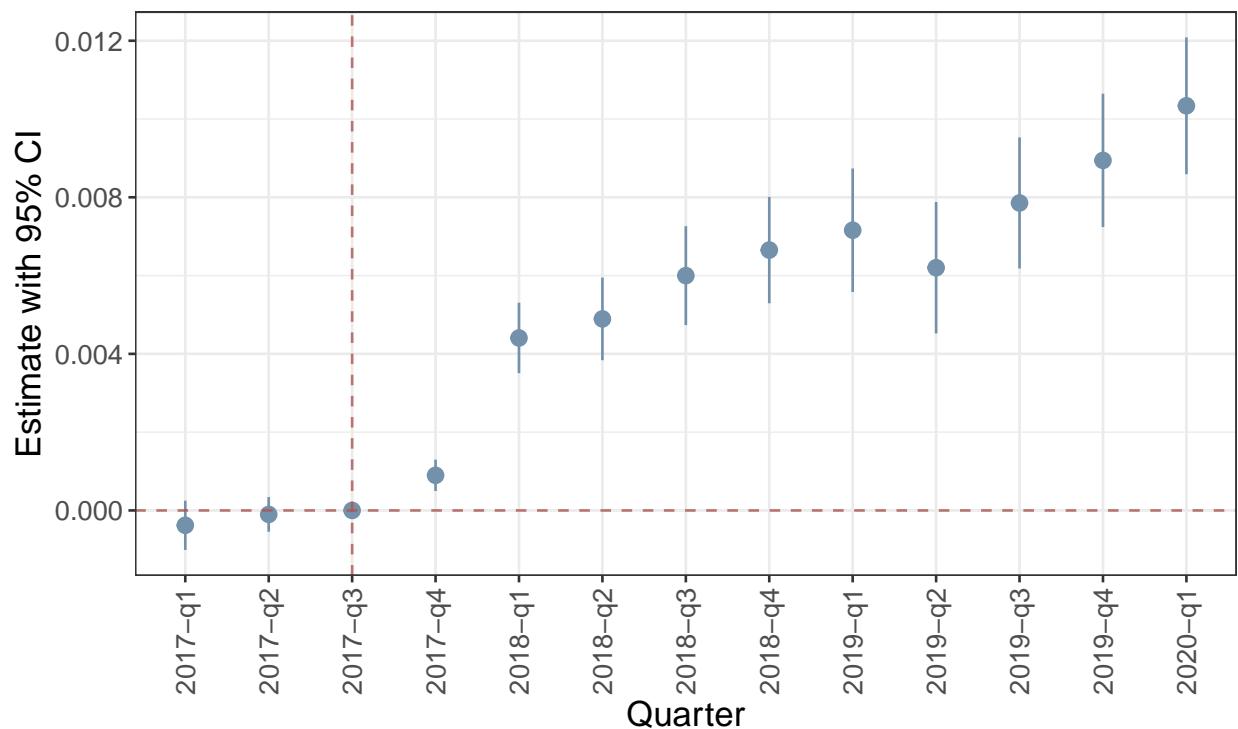
Notes: This figure shows the percentage of households by decile who report gasoline expenditure. To construct the figure we use data from INEGI's Household Income and Expenditure Survey (ENIGH) ([back](#))

Figure 6: Density of stores



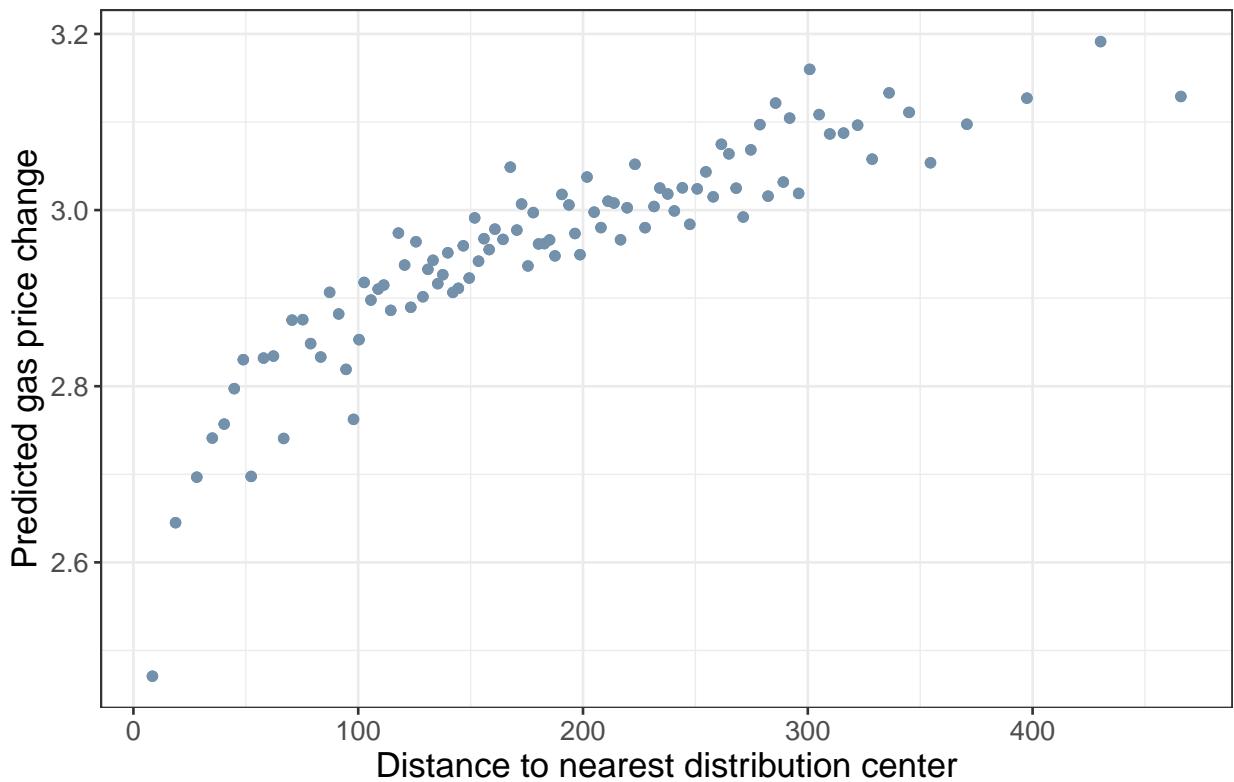
Notes: This figure shows density of stores by municipality. The different colors represent the number of stores per every 100 people. While there is higher density in the center and northern parts of the country, mom-and-pop shops are prevalent everywhere in the country. To construct this map we use our novel dataset that contains coordinate level information on every store. ([back](#))

Figure 7: First Stage by quarter: gas prices



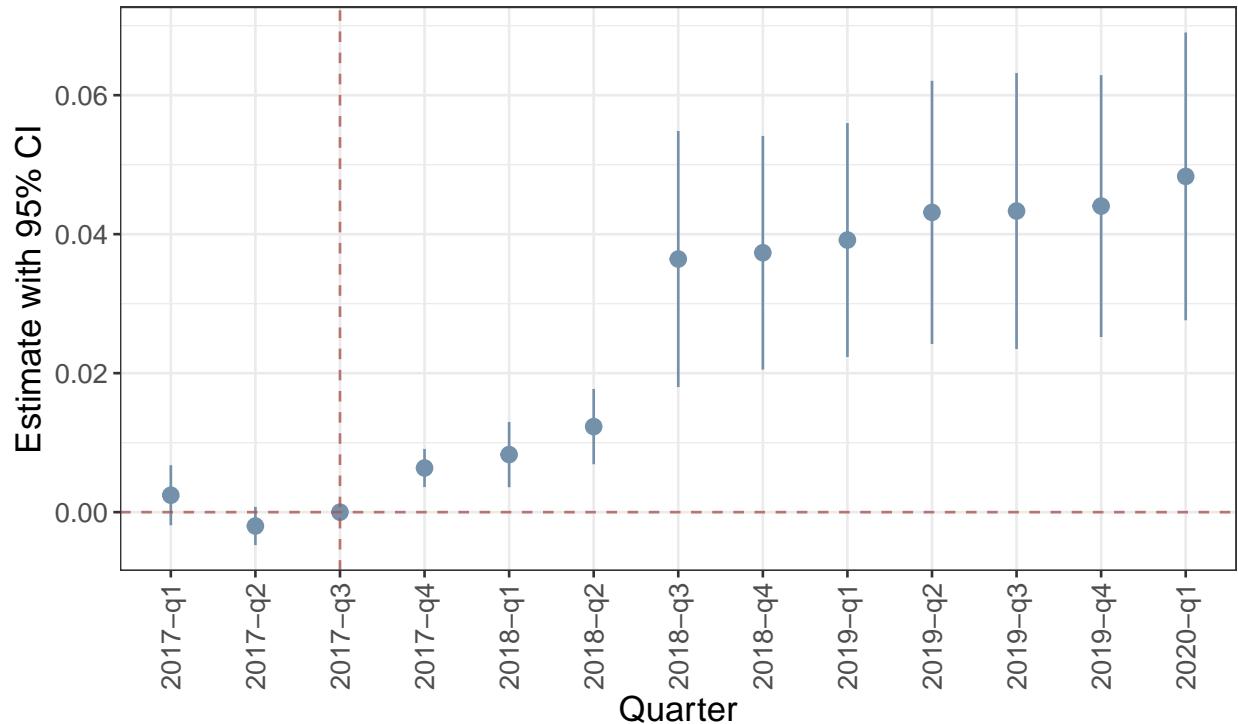
Notes: First stage coefficients of Equation 4. Outcome is log of gasoline price. The regression includes municipality and quarter-by-year fixed effects. Baseline municipality level controls include population, share of cars, income and a remoteness measure that is constructed as the share of people without easy access to a main road. Standard errors clustered at the municipality level. [\(back\)](#)

Figure 8: Binscatter plot of distances to distribution centers and predicted gas prices



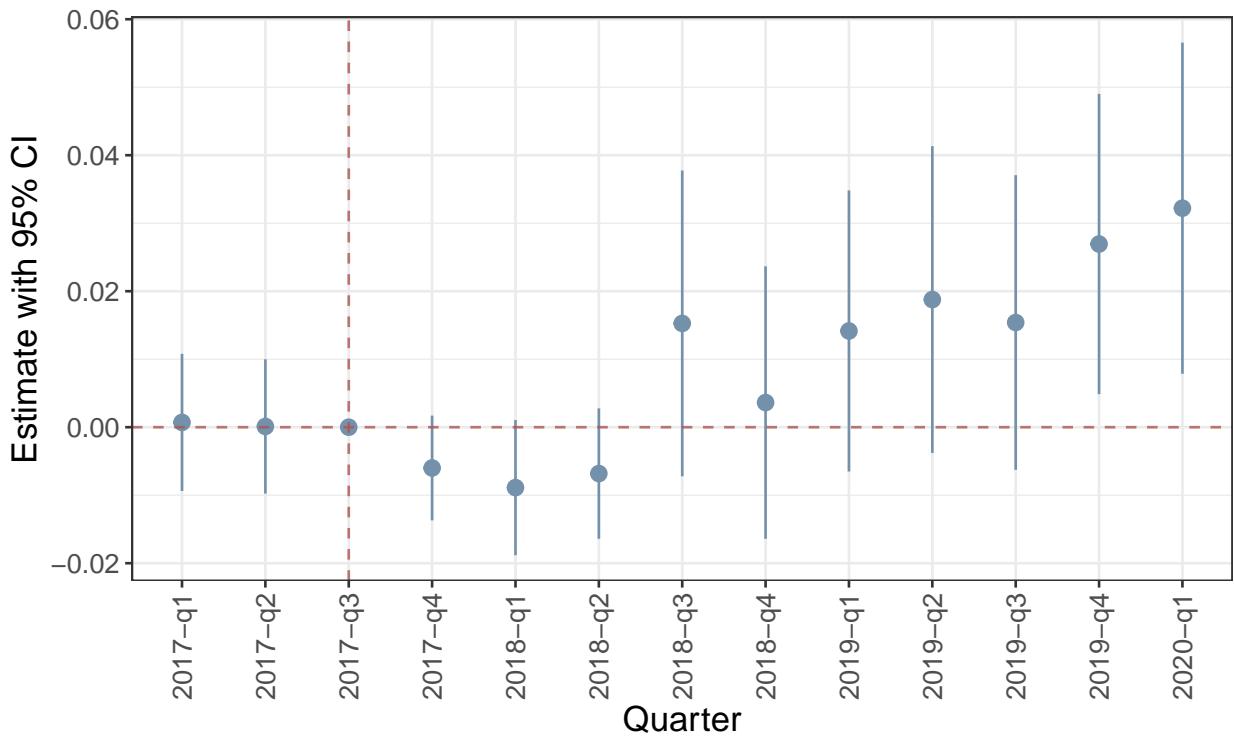
Notes: The x-axis represents the average distance from every gas station in a municipality to the closest distribution center. Each dot in the plot is the bin-mean of the predicted values from running the first stage regression. ([back to first stage discussion](#))

Figure 9: Reduced form by quarter: Stores



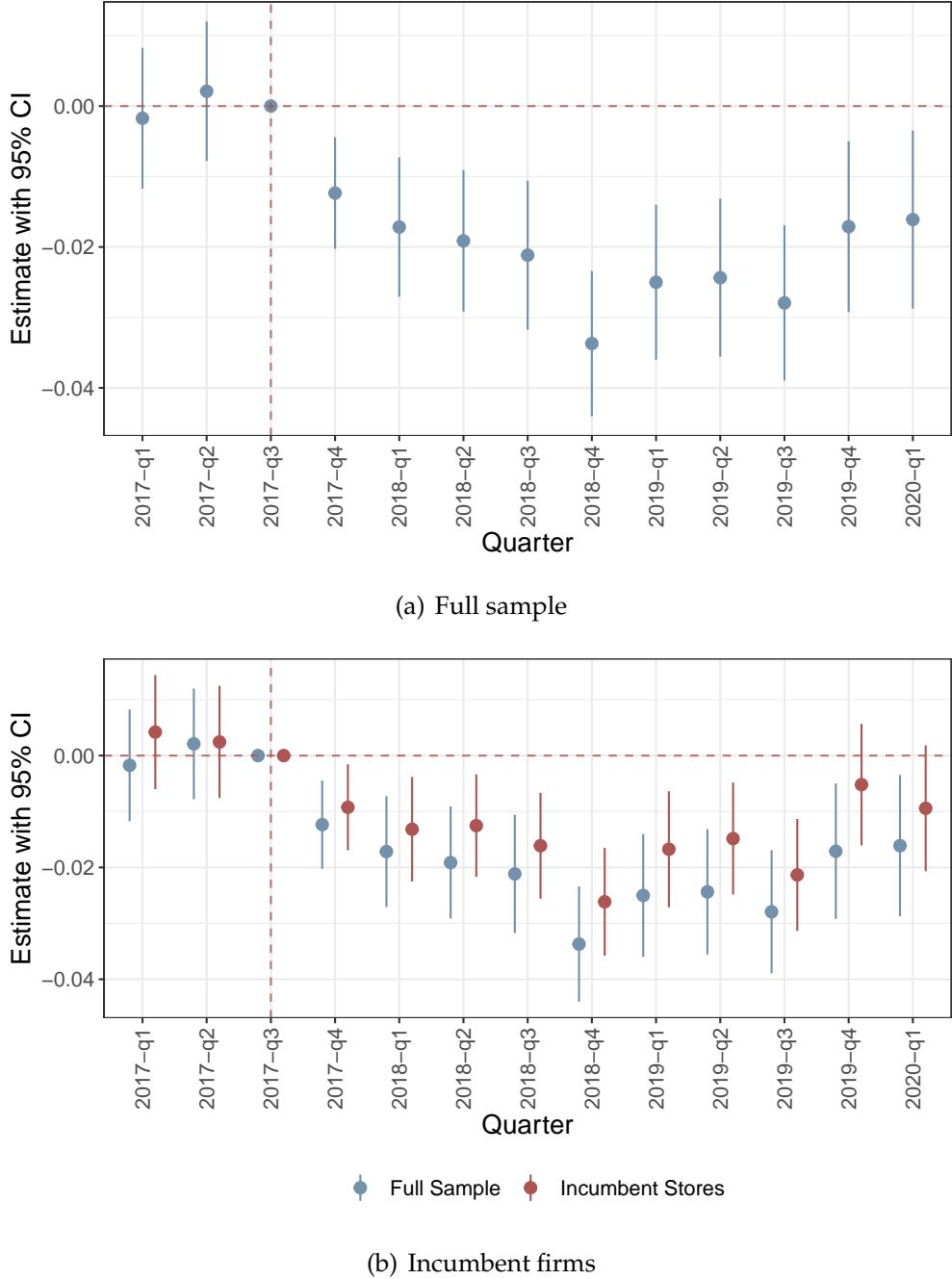
Note: Reduced form coefficients of event-study for Equation 4. Outcome is log number of stores in a quarter in a municipality. The regression includes municipality and quarter-by-year fixed effects. Baseline municipality level controls include population, share of cars, income and a remoteness measure that is constructed as the share of people without easy access to a main road. Standard errors clustered at the municipality level. [\(back\)](#)

Figure 10: Reduced form by quarter: Sales



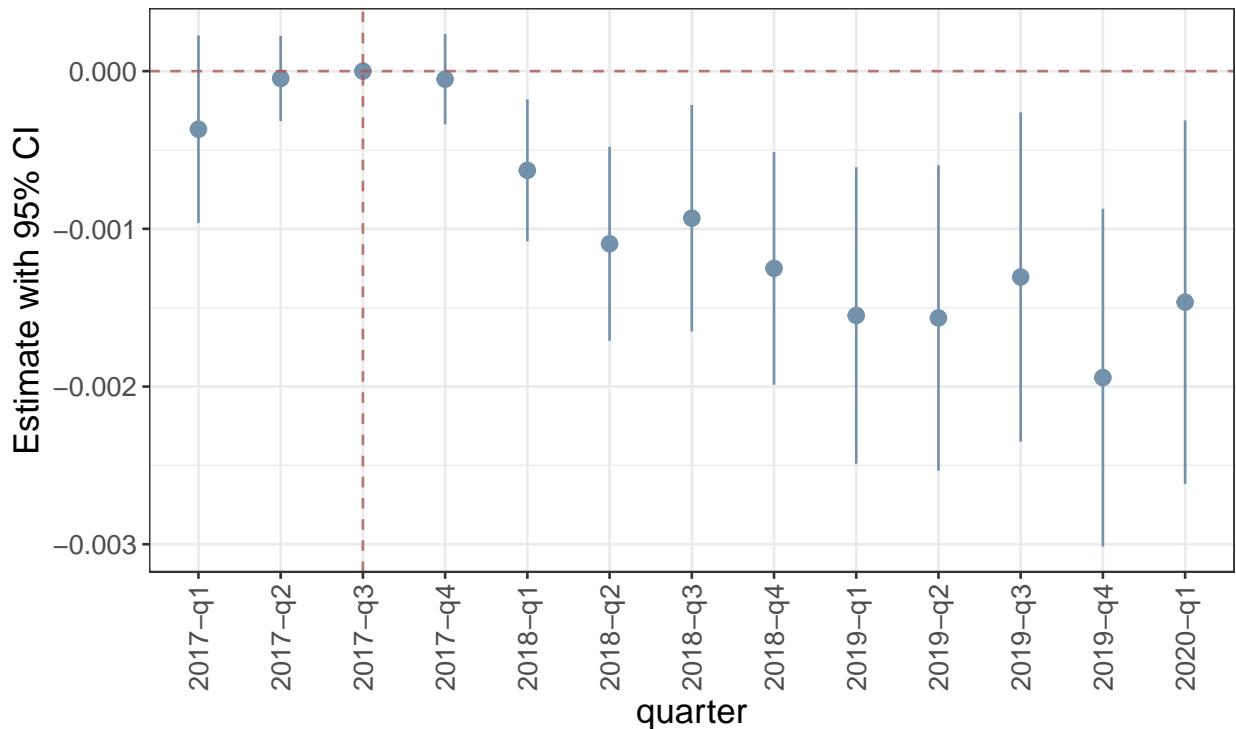
Notes: Reduced form coefficients of event-study for Equation 4. Outcome is log of aggregate sales at mom-and-pop shops in a quarter in a municipality. The regression includes municipality and quarter-by-year fixed effects. Baseline municipality level controls include population, share of cars, income and a remoteness measure that is constructed as the share of people without easy access to a main road. Standard errors clustered at the municipality level. ([back](#))

Figure 11: Reduced form by quarter: Average sales



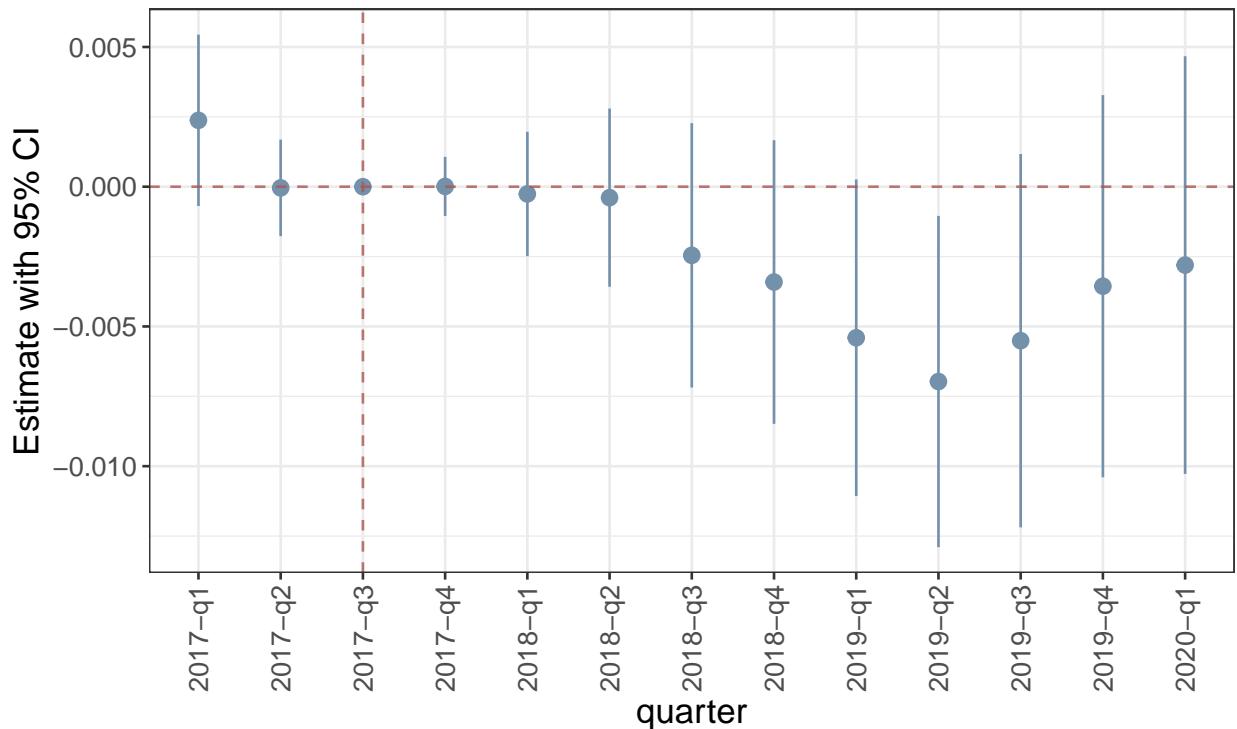
Notes: Reduced form coefficients of event-study for Equation 4. Outcome is log average sales in a quarter in a municipality. Top panel shows results using the full sample and bottom panel adds coefficients from restricting to incumbent firms (as defined by those that were operating before the policy change). Regressions includes municipality and quarter-by-year fixed effects. Baseline municipality level controls include population, share of cars, income and a remoteness measure that is constructed as the share of people without easy access to a main road. Standard errors clustered at the municipality level. (back)

Figure 12: Reduced form by quarter: Quality



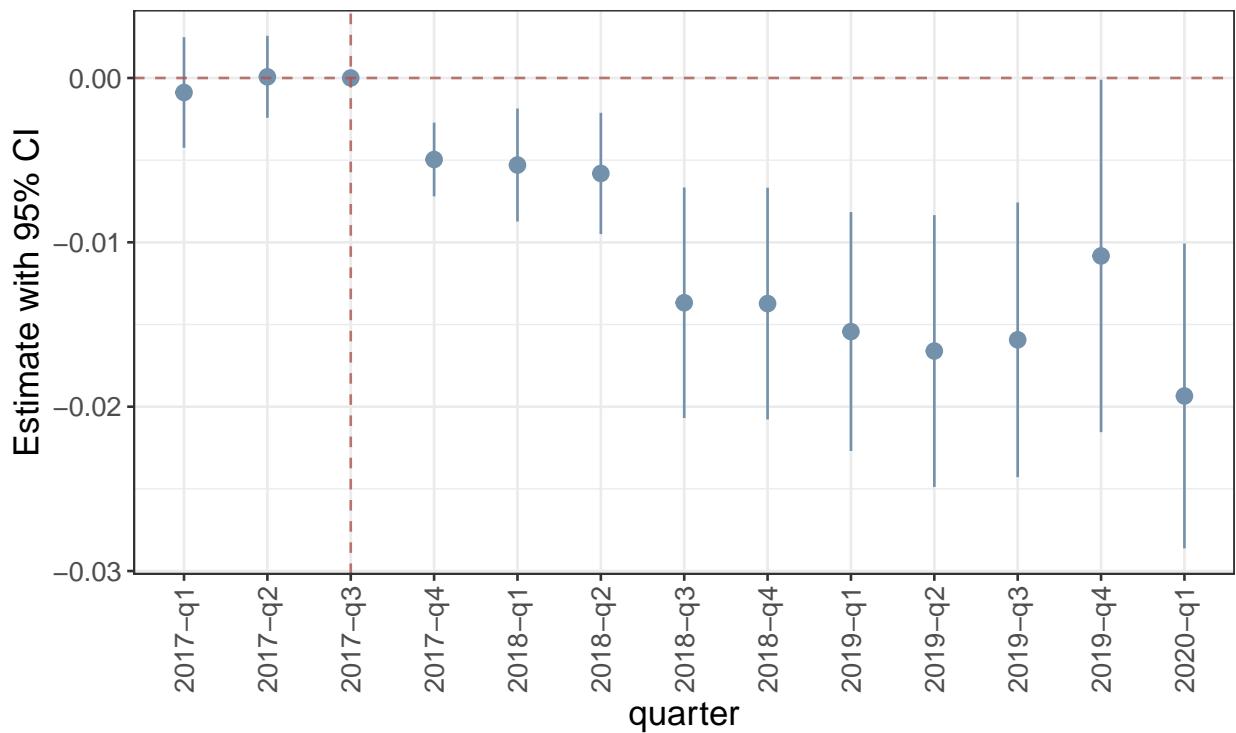
Notes: Reduced form coefficients of event-study for Equation 4. Outcome is normalized quality by municipality. Quality measure is constructed by taking firm-level fixed effect coefficients of Equation 7, variation is coming from change in the composition of existing firms. The regression includes municipality and quarter-by-year fixed effects. Baseline municipality level controls include population, share of cars, income and a remoteness measure that is constructed as the share of people without easy access to a main road. Standard errors clustered at the municipality level. (back)

Figure 13: Reduced form by quarter: fixed cost of entry (rent index)



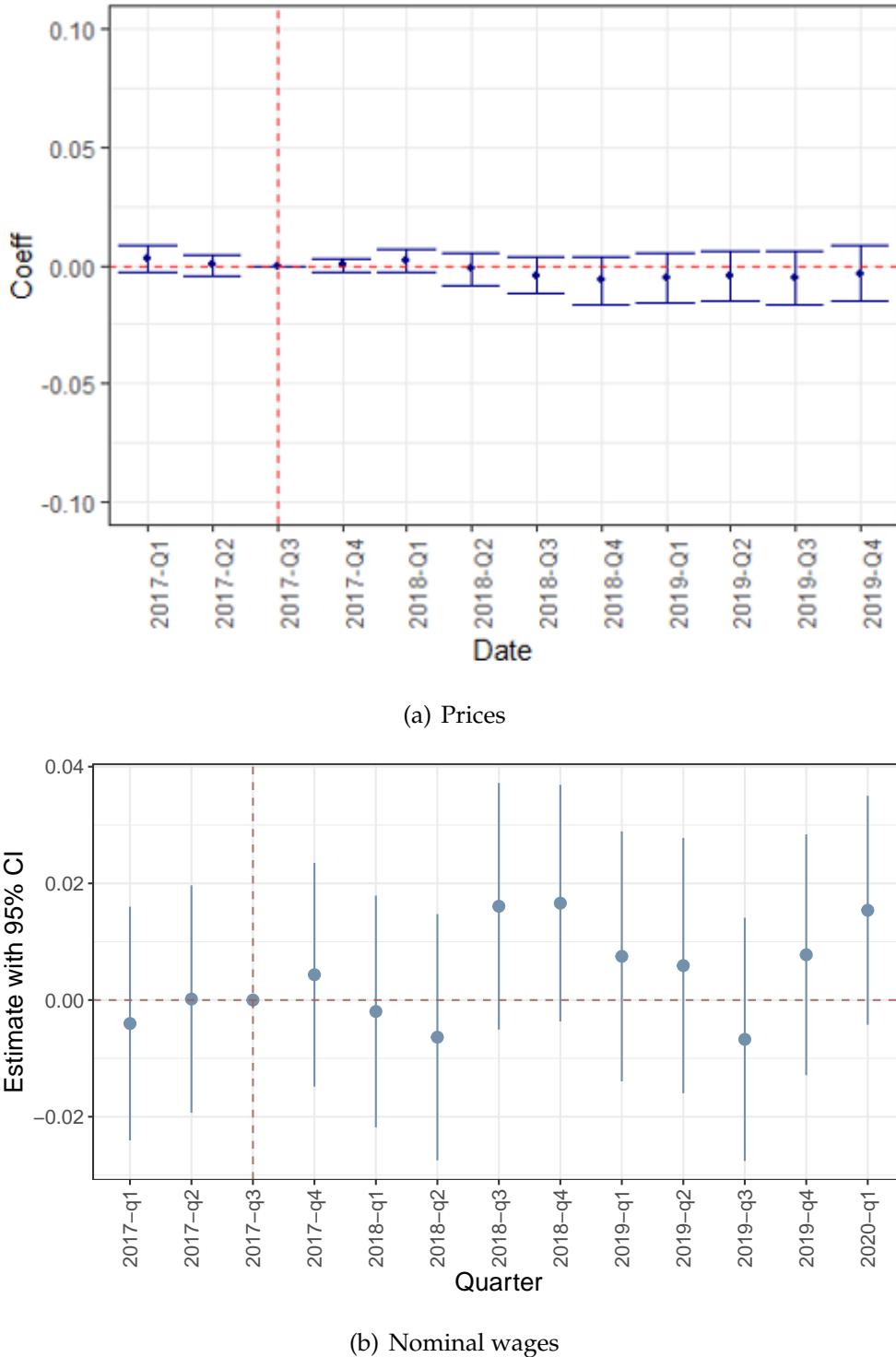
Notes: Reduced form coefficients of event-study for Equation 4. Outcome is normalized fixed cost of entry as measured by our rent index. The regression includes municipality and quarter-by-year fixed effects. Baseline municipality level controls include population, share of cars, income and a remoteness measure that is constructed as the share of people without easy access to a main road. Standard errors clustered at the municipality level. ([back](#))

Figure 14: Average distance traveled to closest store



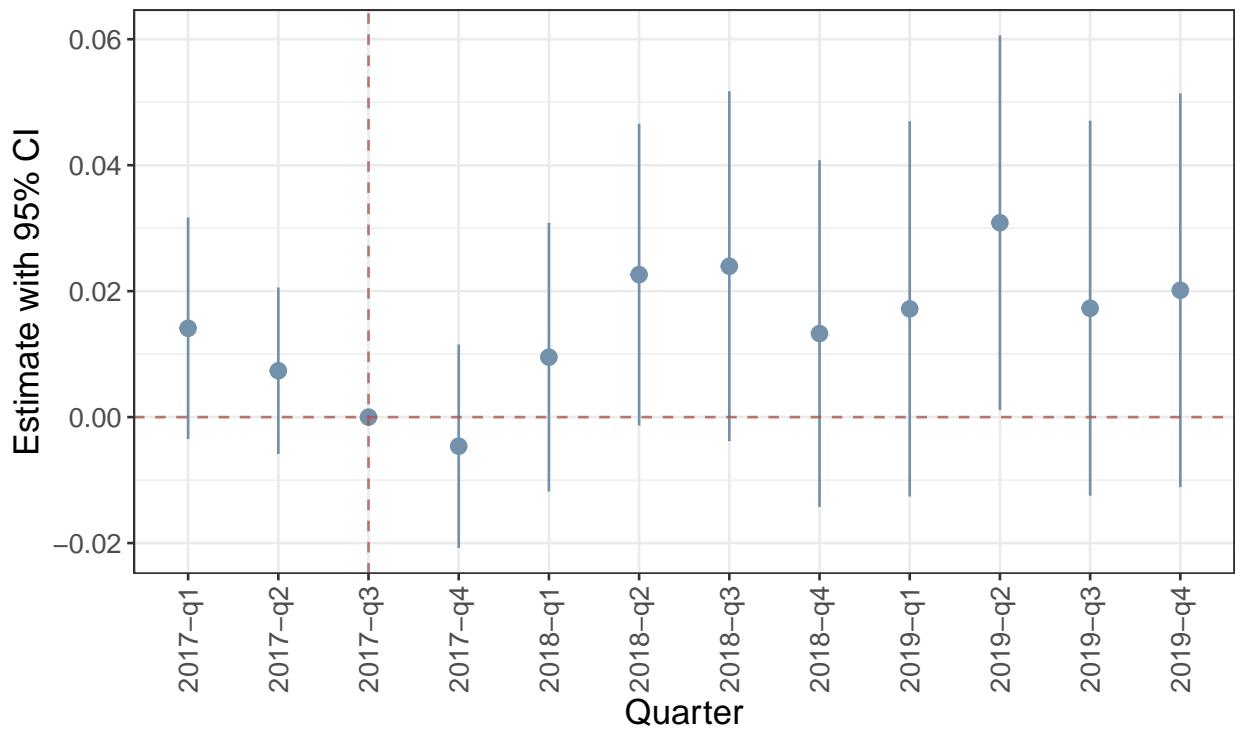
Notes: Reduced form coefficients of event-study for Equation 4. Outcome is log of average distance traveled to closest store. Distance measure is computed from a sample of 1,000 points uniformly distributed across each municipality to the closest store. The regression includes municipality and quarter-by-year fixed effects. Baseline municipality level controls include population, share of cars, income and a remoteness measure that is constructed as the share of people without easy access to a main road. Standard errors clustered at the municipality level. ([back](#))

Figure 15: Evolution of prices and wages after gas price shock



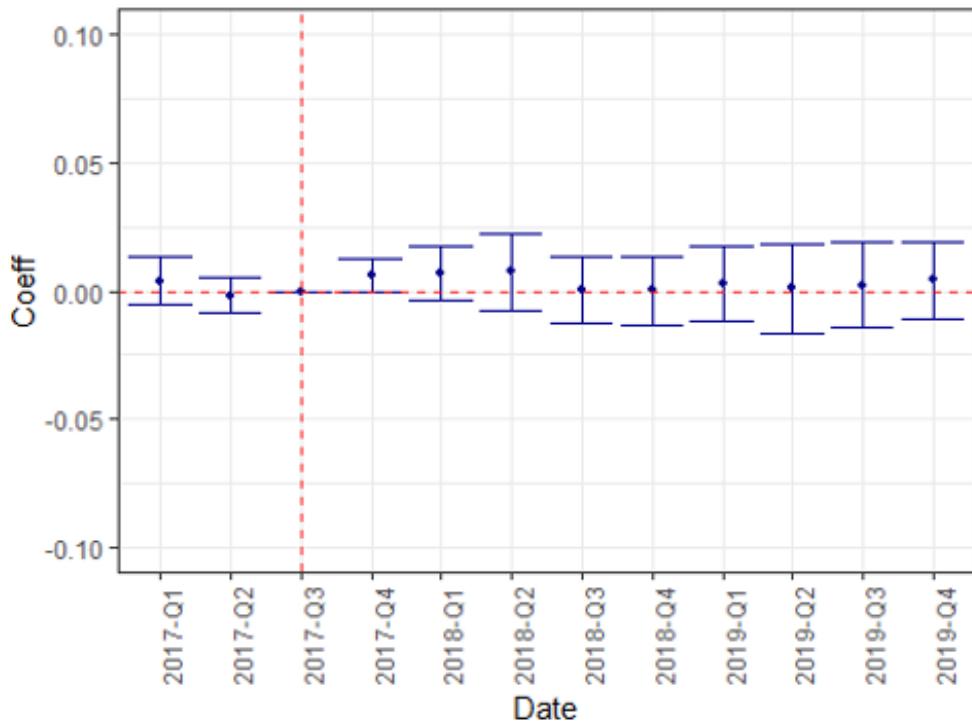
Notes: Panel A shows coefficients for Equation 9 using INEGI's barcode-level price data. Panel B shows coefficients for Equation 4 using Social Security data on wages. Standard errors clustered at the municipality level. (back)

Figure 16: Evolution of employment in formal sector

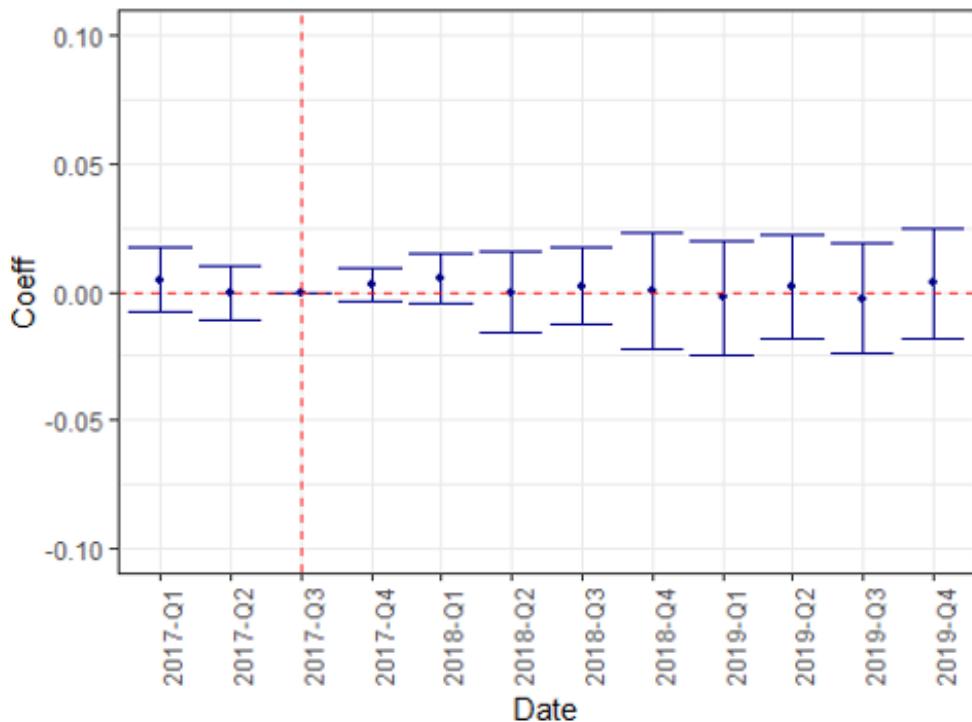


Notes: Reduced form coefficients of event-study for Equation 4. Outcome is employment in the formal sector. The regression includes municipality and quarter-by-year fixed effects. Baseline municipality level controls include population, share of cars, income and a remoteness measure that is constructed as the share of people without easy access to a main road. Standard errors clustered at the municipality level. ([back](#))

Figure 17: Evolution of prices at modern and traditional shops



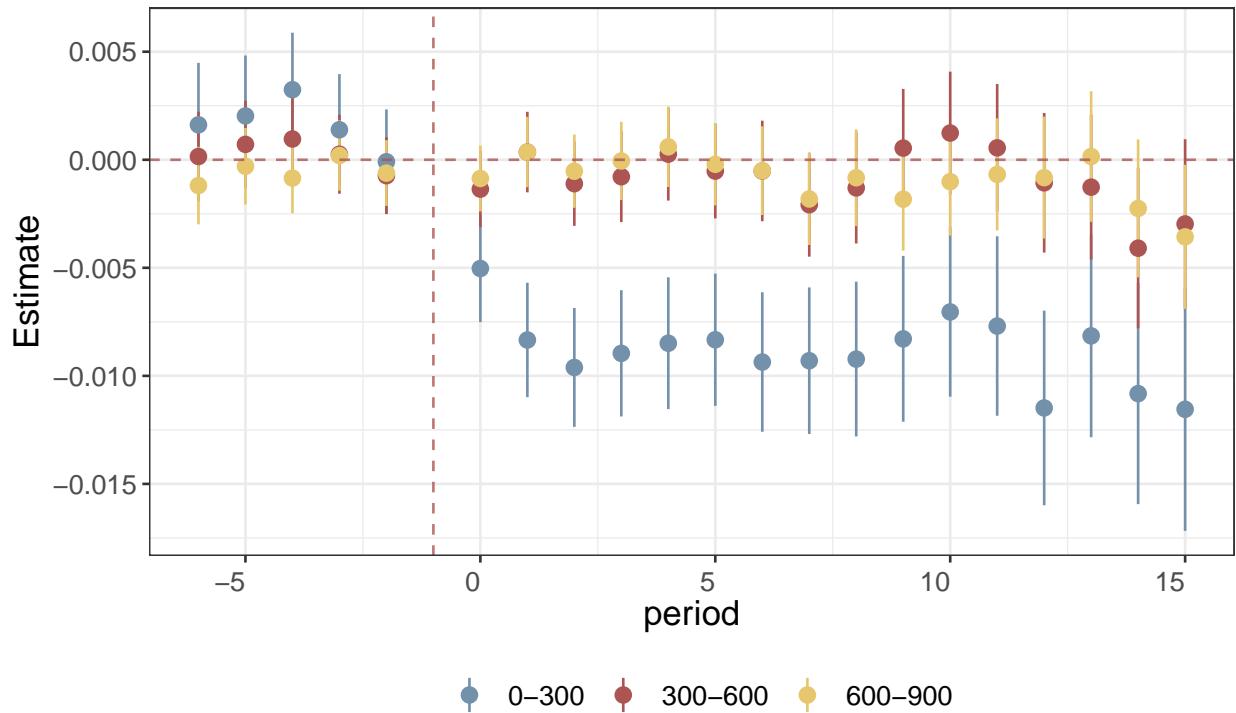
(a) Modern Stores



(b) Traditional Stores

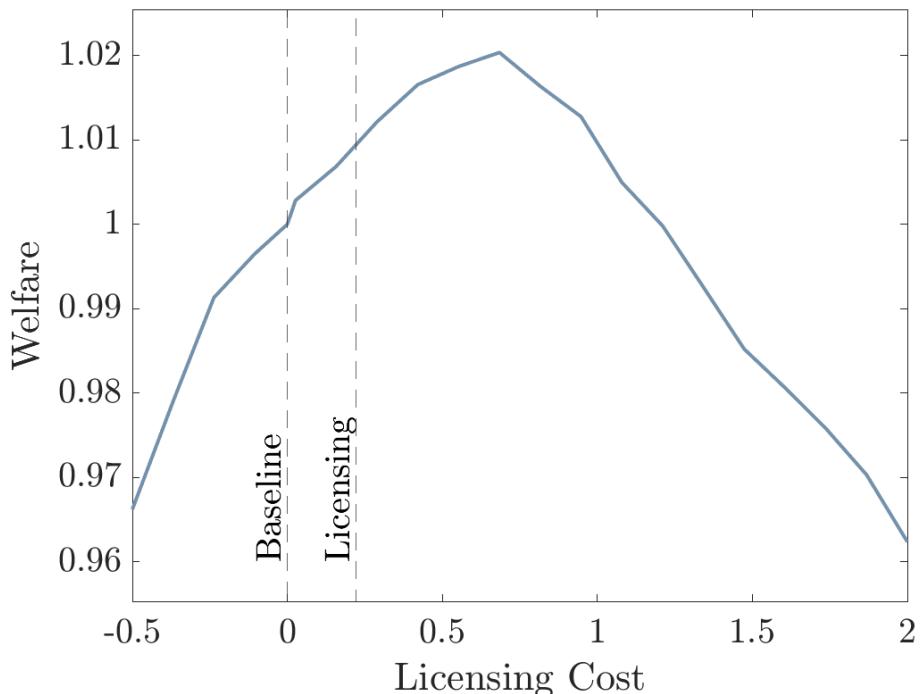
Notes: These figures show coefficients for Equation 9 using INEGI's barcode-level price data. Panel A restricts the sample to only look at prices recorded at modern stores. Panel B restricts the sample to only look at prices recorded at traditional stores. Standard errors clustered at the municipality level. (back)

Figure 18: Spatial Decay of Entry on incumbent's sales



Notes: This figure shows the effect of entry on incumbent's sales. We construct rings around every entrant and estimate the effect of a new store entering on incumbent's sales. We set the period of entry as $t = 0$ for every entrant and use $t = -1$ as the reference group. We include incumbent firm fixed effects and municipality-month fixed effects (back).

Figure 19: Change in welfare under different levels of licensing cost



Notes: This figure shows results from our estimated model of change in welfare under different levels of licensing costs. Negative numbers represent subsidies and positive numbers are taxes. The government makes zero profit and rebates revenue to households. Results are normalized to the baseline case where licensing costs are zero. The dotted line represents the licensing cost imposed by Mexico City's program. Welfare could increase by 1.4% if licenses to operate where required by decreasing the number of stores in the market and thus increasing producer surplus (less business stealing). ([back](#))

Tables

Table 1: Summary statistics

Statistic	Mean	St. Dev.	Pctl(25)	Pctl(50)	Pctl(75)	Max
# of stores/Month	783,335	26,796	754,139	795,673	799,376	831,255
# Stores/Mun	527.7	1,067	88	206	435	12,854
# Stores/1KPop	8.95	5.78	6.38	8.95	11.3	188.5
Market Share	0.003	0.015	0.0002	0.0005	0.002	1
Month Value USD	223	249	63	136	285	1,790
Month Q	416	432	128	274	551	41,580
Average Price USD	0.54	0.5	0.42	0.51	0.59	27
Informal	83%					
Woman owner	63%					
Owns 1 store	82%					

Notes: Table shows summary statistics for key characteristics of our novel data which contains information on every mom-and-pop shop our upstream supplier ever sold to from 2017-2020. When applicable, we converted Mexican Pesos to USD taking a conversion rate of 18 MXN = 1 USD. ([back](#))

Table 2: Market Structure

Dependent Variables:	First Stage		IV	
	Log Gasoline Price (1)	Log #Stores (2)	Log Average Sales (3)	Log Sales (4)
<i>Panel A: Full Sample</i>				
<i>Variables</i>				
Log Distance Distr. Center × Post	0.006*** (0.0006)			
Log Gasoline Price		4.88*** (1.12)	-3.31*** (0.631)	1.57 (1.16)
Controls	Yes	Yes	Yes	Yes
<i>Fit statistics</i>				
Dep Var Mean (pre period)	0.791	438.2	441.0	253,237.6
N Observations	27,767	27,767	27,767	27,767
N Stores	1,114,665	1,114,665	1,114,665	1,114,665
F-test (1st stage)	333.1	333.1	333.1	333.1
<i>Panel B: Municipalities without Supermarkets</i>				
<i>Variables</i>				
Log Distance Distr. Center × Post	0.008*** (0.0010)			
Log Gasoline Price		5.85*** (1.43)	-4.22*** (0.875)	1.63 (1.47)
Controls	Yes	Yes	Yes	Yes
<i>Fit statistics</i>				
Dep Var Mean (pre period)	0.792	317.8	433.5	177,422.9
N Observations	20,303	20,303	20,303	20,303
N Stores	1,114,665	1,114,665	1,114,665	1,114,665
F-test (1st stage)	263.8	263.8	263.8	263.8
<i>Fixed-effects</i>				
Quarter-Year	Yes	Yes	Yes	Yes
Municipality	Yes	Yes	Yes	Yes

Clustered (Municipality) standard-errors in parentheses

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Notes: Column 1 shows estimates of Equation 3 in the main text with log gasoline price as outcome. Columns 2-4 show IV estimates of Equation 5, using distance to distribution centers as the instrument. The outcomes of interest are total number of m&p in a municipality (Column 2), the average size of a m&p as measured by average sales (Column 3) and aggregate m&p sales (Column 4). Baseline municipality level controls include population, income, share of cars and a remoteness measure constructed as the share of people without access to a main road. Dependent variable means are in USD (except number of stores), taking a conversion rate of 20 MXN = 1 USD. F-stat corresponds to Olea and Pflueger (2013) effective F-statistic. Panel A reports results for the full sample and Panel B restricts to municipalities without a supermarket. (back to first stage discussion) (back to #stores)

Table 3: IV: Entry and Exit

Dependent Variables:	Without Controls		With Controls	
	#Entry Stores	#Exit Stores	#Entry Stores	#Exit Stores
	(1)	(2)	(3)	(4)
<i>Variables</i>				
Log Gasoline Price	11.6*** (2.08)	-1.45 (1.90)	13.4*** (2.49)	-0.732 (2.29)
<i>Fixed-effects</i>				
Quarter-Year	Yes	Yes	Yes	Yes
Municipality	Yes	Yes	Yes	Yes
<i>Fit statistics</i>				
N Observations	27,928	27,928	27,767	27,767
N Stores	1,114,665	1,114,665	1,114,665	1,114,665
Dep. Var. Mean	17.2	12.0	17.2	12.0

Clustered (Municipality) standard-errors in parentheses

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Notes: IV estimates of Equation 5 in main text. Outcomes are the hyperbolic arcsine of the number of entries (Column 1 and 3) and exits (Column 2 and 4). For columns 3 and 4 we include the following baseline municipality level controls: population, income, share of cars and a remoteness measure constructed as the share of people without access to a main road. (back)

Table 4: IV: Market Structure Effects by terciles of distance to modern supermarket

Dependent Variables: Tercile:	Log Sales			Log Stores			Log Average Sales		
	T1	T2	T3	T1	T2	T3	T1	T2	T3
<i>Variables</i>									
Log Gasoline Price	0.522 (1.20)	2.91 (2.04)	-1.58** (0.755)	2.32* (1.21)	5.28*** (1.95)	2.28*** (0.831)	-2.06** (0.818)	-1.71 (1.07)	-3.86*** (0.930)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Fixed-effects</i>									
Quarter-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>									
Dep Var Mean (pre period)	323,306.8	59,946.1	32,916.8	572.3	143.8	74.1	467.2	410.9	421.6
Avg Dist Supermarket (km)	5.50	17.1	40.8	5.50	17.1	40.8	5.50	17.1	40.8
N Observations	9,271	9,270	9,161	9,271	9,270	9,161	9,271	9,270	9,161
F-test (1st stage), Log Gasoline Price	112.0	143.6	215.3	112.0	143.6	215.3	112.0	143.6	215.3
Hyp. Test pooled(T1, T2) = T3	2.871 (p-value=0.09)			1.054 (p-value=0.305)			2.992 (p-value=0.084)		

Clustered (Municipality) standard-errors in parentheses

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Notes: This table shows the effect of aggregate sales at mom and pop shops (first three columns), number of stores (columns 4-6) and average sales (last three columns) separately by terciles of distance to the closest supermarket. The first tercile represents municipalities that are have a supermarket close by (on average 5.5 km), the second tercile has a supermarket at an average distance of 17 km, while the third tercile represents municipalities with a supermarket very far away (on average 40.8 km). For all outcomes we see an inverted U-shaped effect. For sales and average sales we can confirm that terciles 1 and 3 are significantly different from tercile 2. ([back](#))

Table 5: IV: Heterogeneity by baseline number of stores

Dependent Variables:	Log #Stores (1)	Log Average Sales (2)
<i>Variables</i>		
Log Gasoline Price	4.73*** (1.05)	-3.13*** (0.587)
Log Gasoline Price \times Q2	-0.228** (0.105)	0.063 (0.086)
Log Gasoline Price \times Q3	-0.475*** (0.129)	0.191** (0.096)
Log Gasoline Price \times Q4	-0.703*** (0.159)	0.392*** (0.110)
Log Gasoline Price \times Q5	-1.24*** (0.230)	0.672*** (0.152)
Controls	Yes	Yes
<i>Fixed-effects</i>		
Quarter-Year	Yes	Yes
Municipality	Yes	Yes
<i>Fit statistics</i>		
N Observations	27,767	27,767
N Stores	1,114,665	1,114,665
Dep. Var. Mean	438.2	441.0

Clustered (Municipality) standard-errors in parentheses

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Note: IV estimates of Equation 6. Outcomes are log number of stores in a municipality (Column 1) and log average sales (Column 2). We interact the independent variable log gasoline price with quintiles of baseline number of stores. We include as baseline municipality level controls population, income, share of cars and a remoteness measure constructed as the share of people without access to a main road. In places with more stores at baseline (higher quintiles) we see less entry and thus a smaller business stealing effect. ([back](#))

Table 6: Shopping behavior: substitution across store type

Dependent Variables:	Extensive Margin		Frequency		Intensive Margin	
	M&P	Supermarket	Low	High	Log M&P USD	Log Super USD
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Variables</i>						
Log Gasoline Price	0.032 (0.116)	-0.048 (0.177)	-0.381 (0.326)	0.059 (0.076)	-0.505 (0.537)	-0.404 (0.421)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
<i>Fixed-effects</i>						
State-Year	Yes	Yes	Yes	Yes	Yes	Yes
Municipality	Yes	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>						
Dep Var Mean (pre period)	0.900	0.700	0.690	0.040	152.8	128.5
N Observations	190,758	190,758	190,758	190,758	175,592	130,447
Wald (1st stage), Log Gasoline Price	7.8	7.8	7.8	7.8	6.8	10.5

Clustered (Municipality) standard-errors in parentheses

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Notes: IV estimates of Equation 8. Data comes from INEGI's income and expenditure survey (ENIGH) from 2016, 2018 and 2020. The first two columns show extensive margin results where the outcome variables take values of 1 if there was household expenditure in that category or 0 otherwise. Columns 3 and 4 report whether the household reported shopping monthly, twice a month, or weekly (low frequency) or daily or biweekly (high frequency). While not significant, both sets of outcomes point towards substitution from supermarkets to mom-and-pop shops. Columns 5 and 6 show intensive margin results. We include a rich set of household level controls and municipality controls of the number of supermarkets and mom-and-pop shops present at baseline. (back)

Table 7: Mode of transportation: extensive and intensive margin

Dependent Variables:	Mobility Behavior				Within M&P Substitution Distance Traveled (5)
	Gasoline (1)	Pub Trans (2)	Log Gasoline Lts (3)	Log Pub Trans USD (4)	
<i>Variables</i>					
Log Gasoline Price	-0.231 (0.142)	0.485*** (0.183)	-0.965*** (0.266)	0.949 (0.998)	-1.80** (0.742)
Controls	Yes	Yes	Yes	Yes	Yes
<i>Fixed-effects</i>					
State-Year	Yes	Yes	Yes	Yes	Yes
Municipality	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>					
Dep Var Mean (pre period)	0.440	0.560	104.9	64.4	4,642.8
N Observations	190,758	190,758	87,360	97,150	27,371
F-test (1st stage), Log Gasoline Price	40,492.1	40,492.1	26,006.9	10,439.9	38.7

Clustered (Municipality) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: IV estimates of Equation 8. All data comes from INEGI's income and expenditure survey (ENIGH) for years 2016, 2018 and 2020. The first two columns show extensive margin results where the outcome variables take values of 1 if there was household expenditure in that category or 0 otherwise. The next two columns show intensive margin results. Column 3 is in liters of gasoline consumed while Column 4 is in USD. Column 5 shows the decrease in average distance travel from a (potential) household to the closest mom-and-pop shop. For this regression we include as baseline municipality level controls population, income, share of cars and a remoteness measure constructed as the share of people without access to a main road. [\(back\)](#)

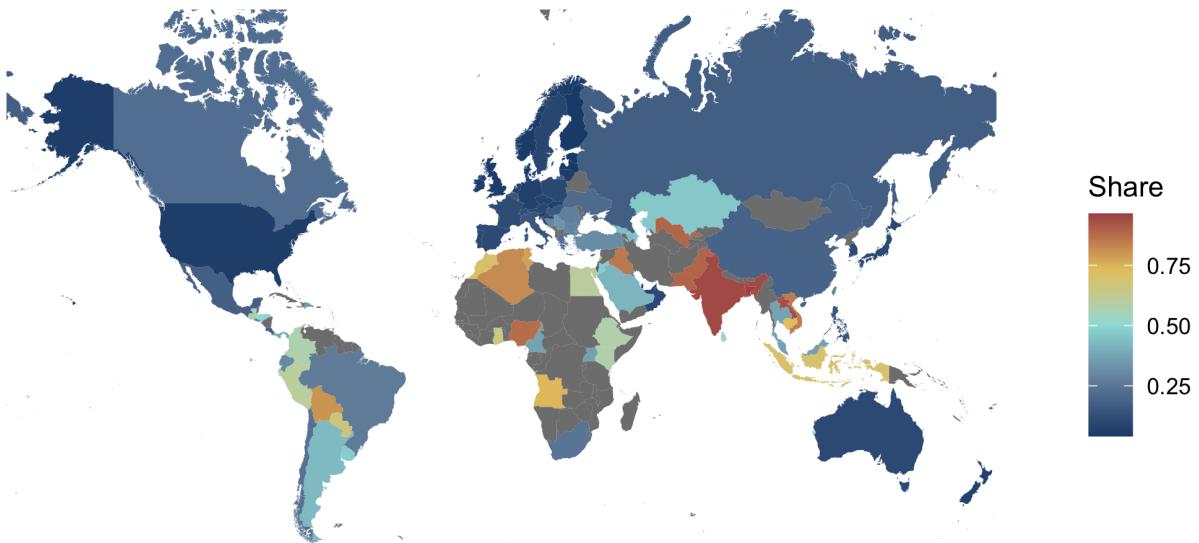
Table 8: Counterfactual: changing transport costs and fixed costs of entry

Changing τ			
	Least Conservative	Medium	Most Conservative
Δ stores	-0.21	-0.13	-0.03
Changing F			
	Least Conservative	Medium	Most Conservative
Δ stores	-0.24	-0.14	-0.03
Changing τ and F			
	Least Conservative	Medium	Most Conservative
Δ stores	-0.41	-0.23	-0.07

Notes: With our estimated model we simulate the number of stores that would exist in the market under three different scenarios of transport costs and fixed cost of entry. The first column represents the least conservative estimate of the difference between transport costs and fixed costs of entry in Mexico and the US while the last column represents the most conservative estimates. [\(back\)](#)

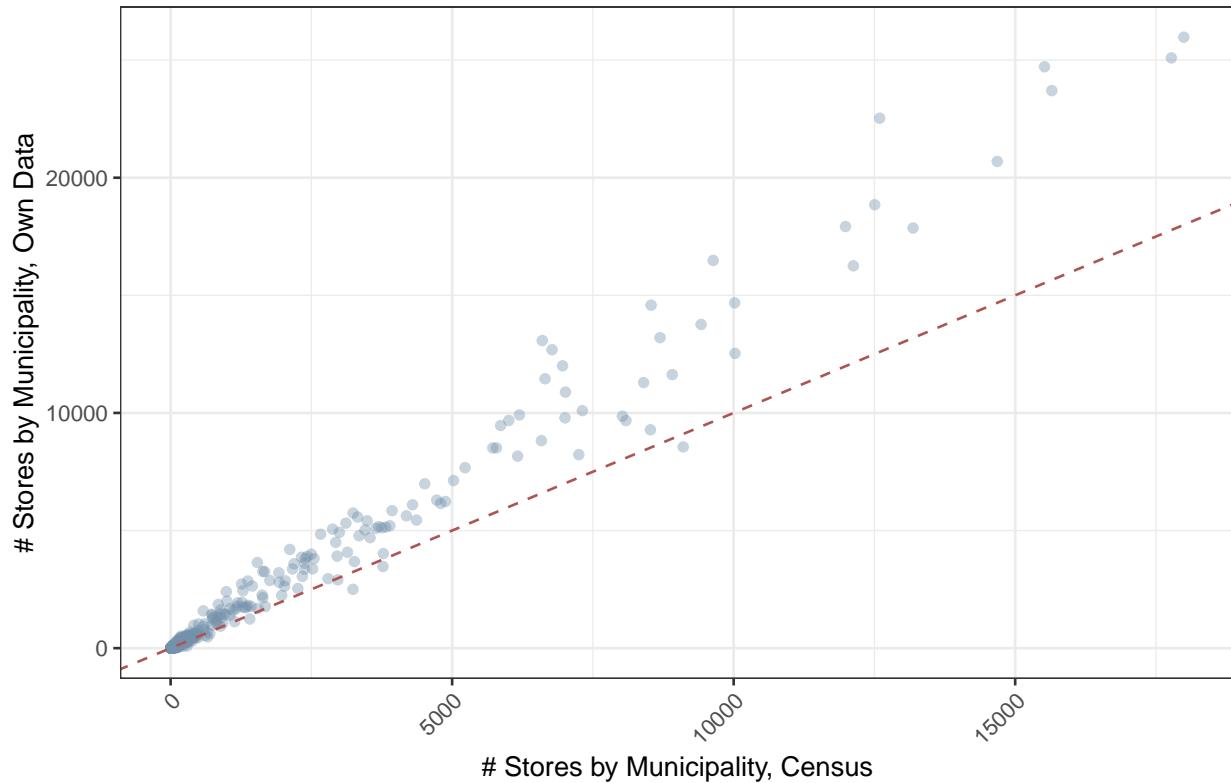
A Additional Figures

Figure A.1: Share of all Food Retail in Traditional Stores



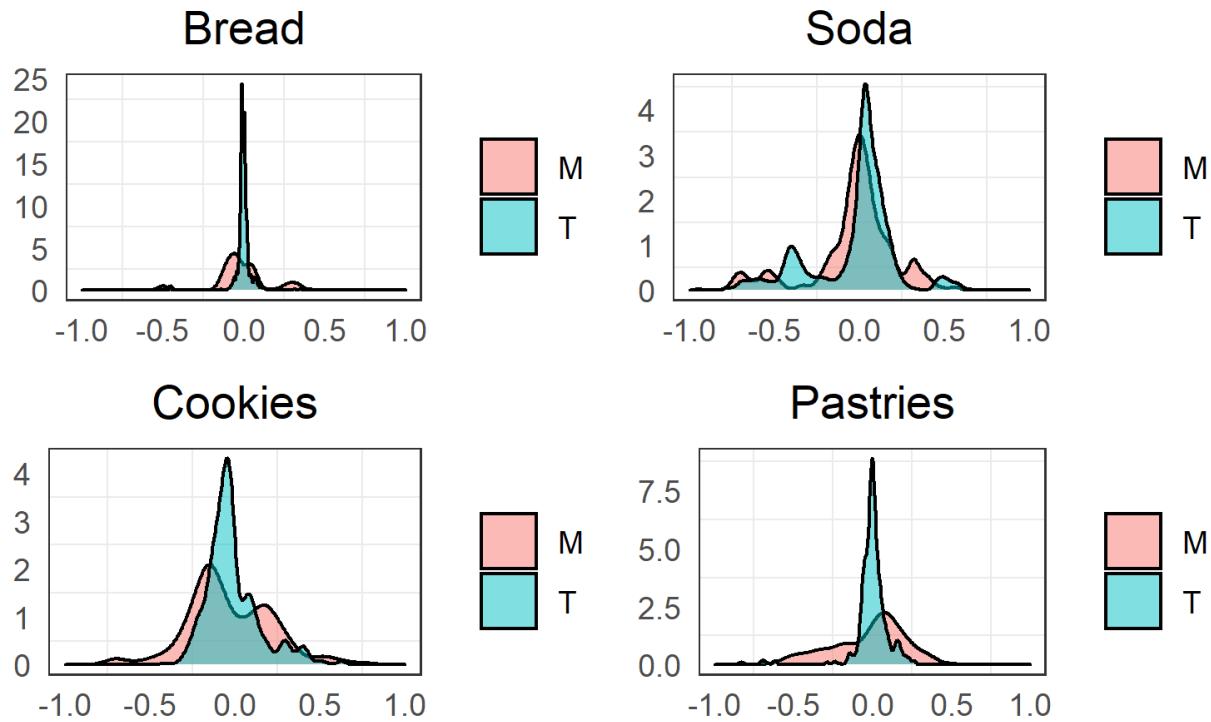
Notes: This figure shows the share of all food retail that is done in traditional stores. Data used to construct this map comes from Euromonitor's 2019 report. Countries in gray indicate that no data was available.
(back)

Figure A.2: Comparison of stores in our data and the census



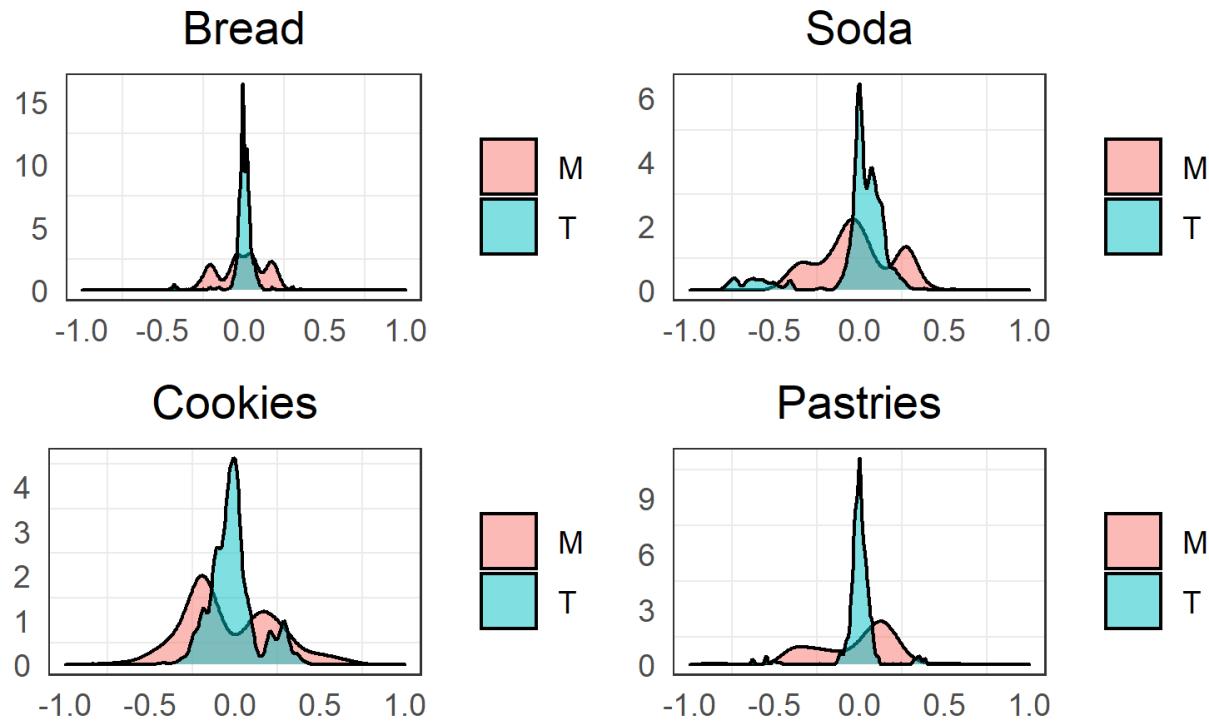
Notes: We plot the number of mom-and-pop shops contained in our data in 2019 for every municipality (y-axis) against the number of shops that appear in INEGI's 2019 DENUE. The DENUE is the official registry of firms which comes from the Economic Census of 2015 and is updated yearly. Each dot represents a different municipality. In red we add a 45 degree line for easier interpretation. Our data is on average better at capturing the total quantity of stores than what is recorded in the census. ([back to setting](#)) ([back to data](#))

Figure A.3: Price densities by store format



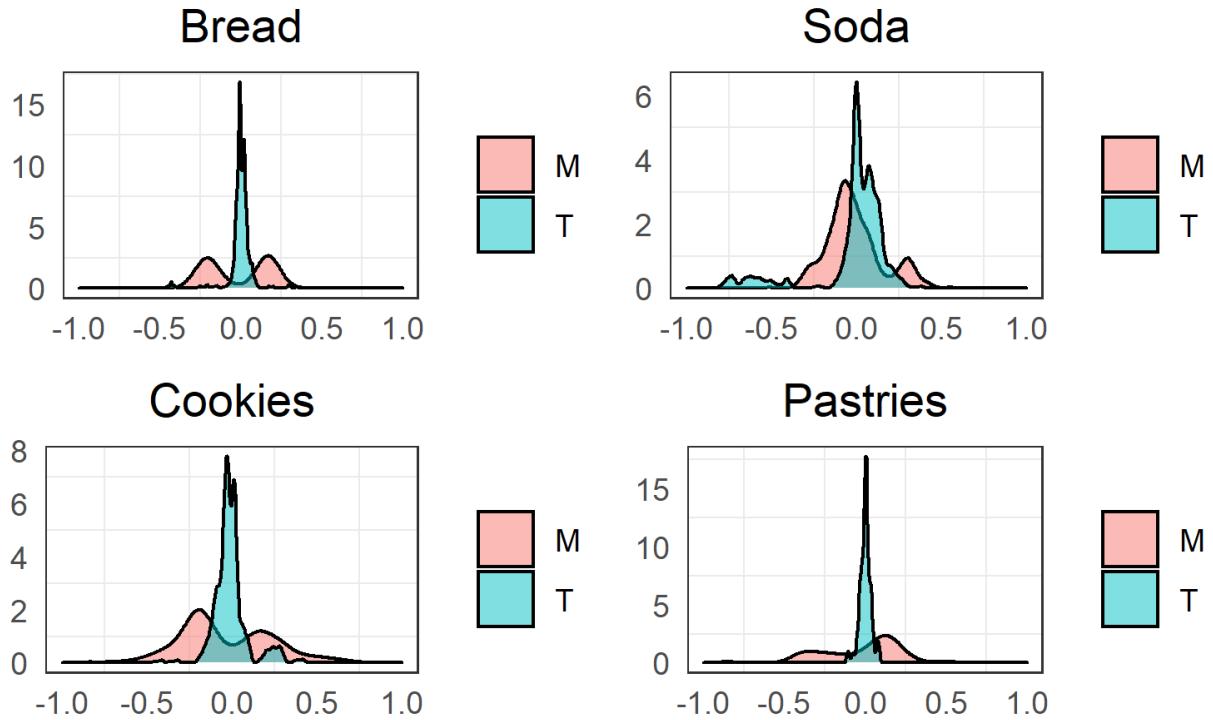
Notes: Figure displays kernel estimates of the log price distribution pooled over store format and months. Log prices refer to final consumer prices and are expressed as deviations from the month's average. All the variation observed is within month. T refers to traditional shops and M refers to modern stores. The underlying data comes from confidential CPI data obtained at INEGI's data lab. (back to model) (back to data)

Figure A.4: Price densities by store format. Within month-state variation.



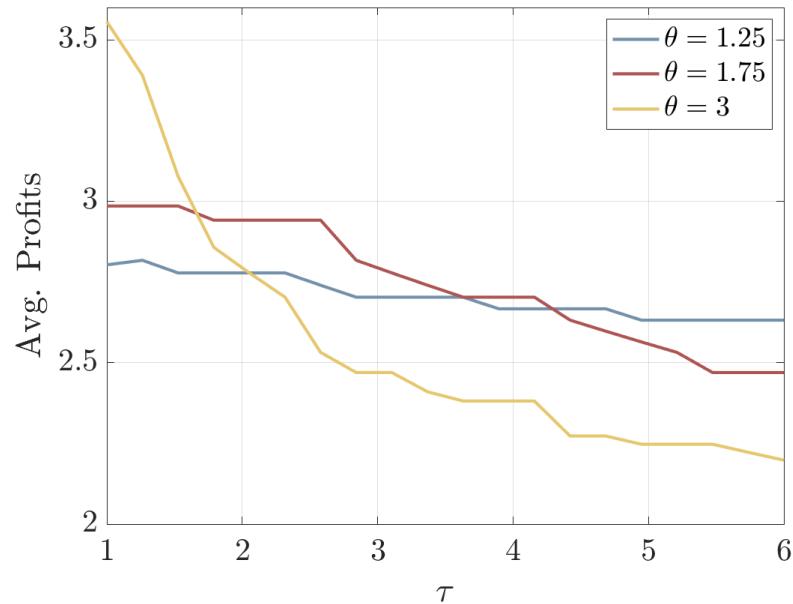
Notes: Figure displays kernel estimates of the log price distribution pooled over store format and months. Log prices refer to final consumer prices and are expressed as deviations from the month-state average. All the variation observed is within month-state. T refers to traditional shops and M refers to modern stores. The underlying data comes from confidential CPI data obtained at INEGI's data lab. ([back to model](#))

Figure A.5: Price densities by store format. Within month-municipality variation.

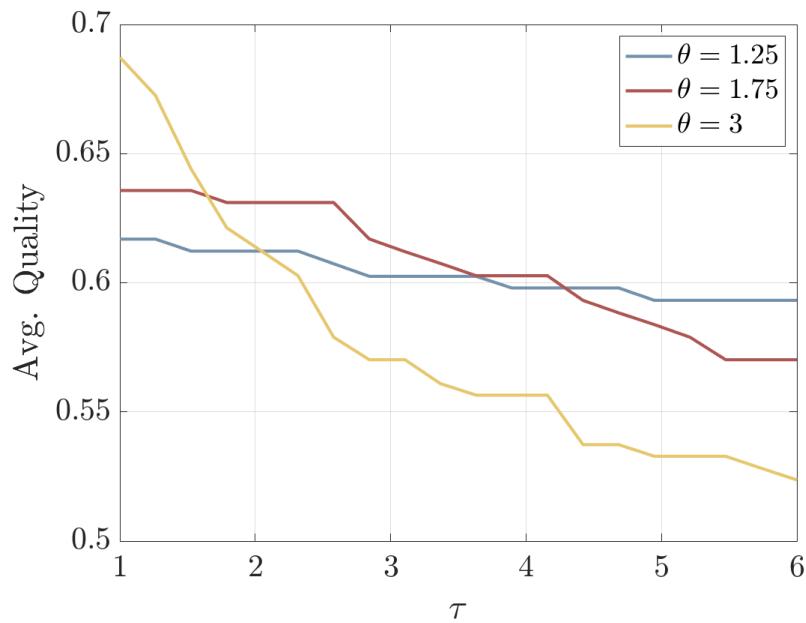


Notes: Figure displays kernel estimates of the log price distribution pooled over store format and months. Log prices refer to final consumer prices and are expressed as deviations from the month-municipality average. All the variation observed is within month-municipality. T refers to traditional shops and M refers to modern stores. The underlying data comes from confidential CPI data obtained at INEGI's data lab. ([back to model](#))

Figure A.6: Impact of increasing consumer transport costs under different values of θ



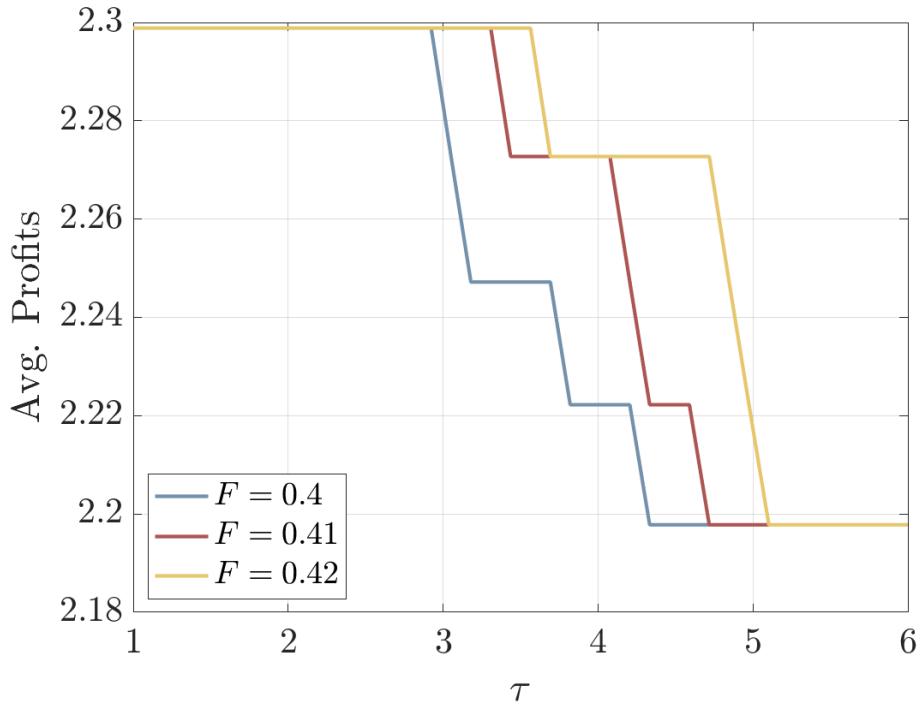
(a) Effect on profits



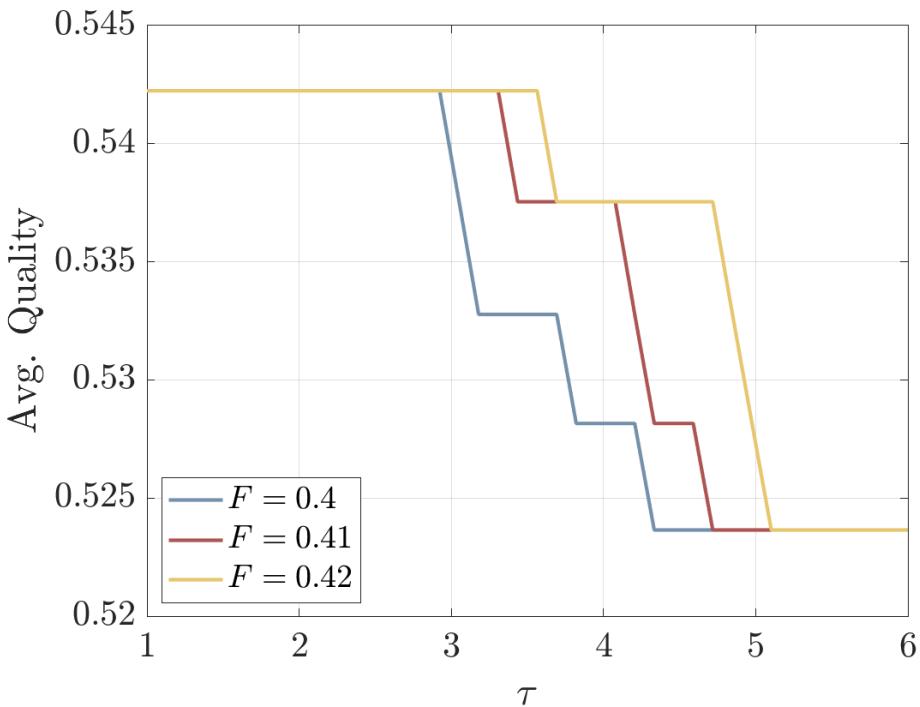
(b) Effect on quality

Notes: These figures are simulations using the model to show how increases in transport costs affect average profits (Panel A) and average quality (Panel B) for different value of θ . When θ is high, increases in transport costs lead to a larger drop in profits and quality. ([back](#))

Figure A.7: Impact of increasing consumer transport costs under different values of F



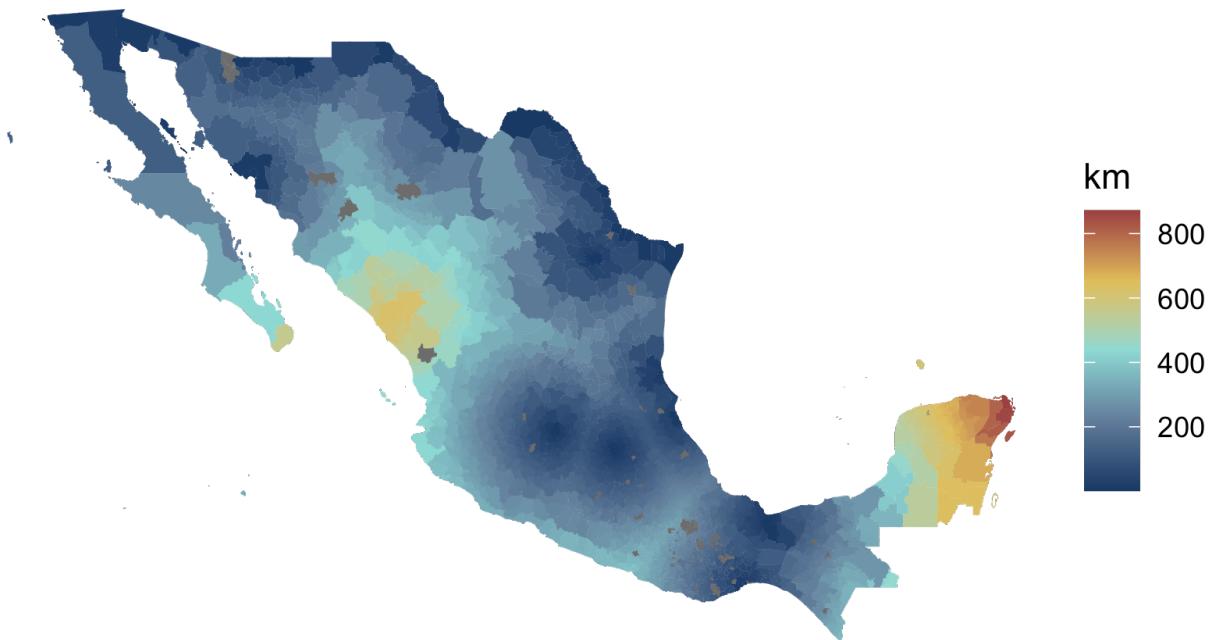
(a) Effect on profits



(b) Effect on quality

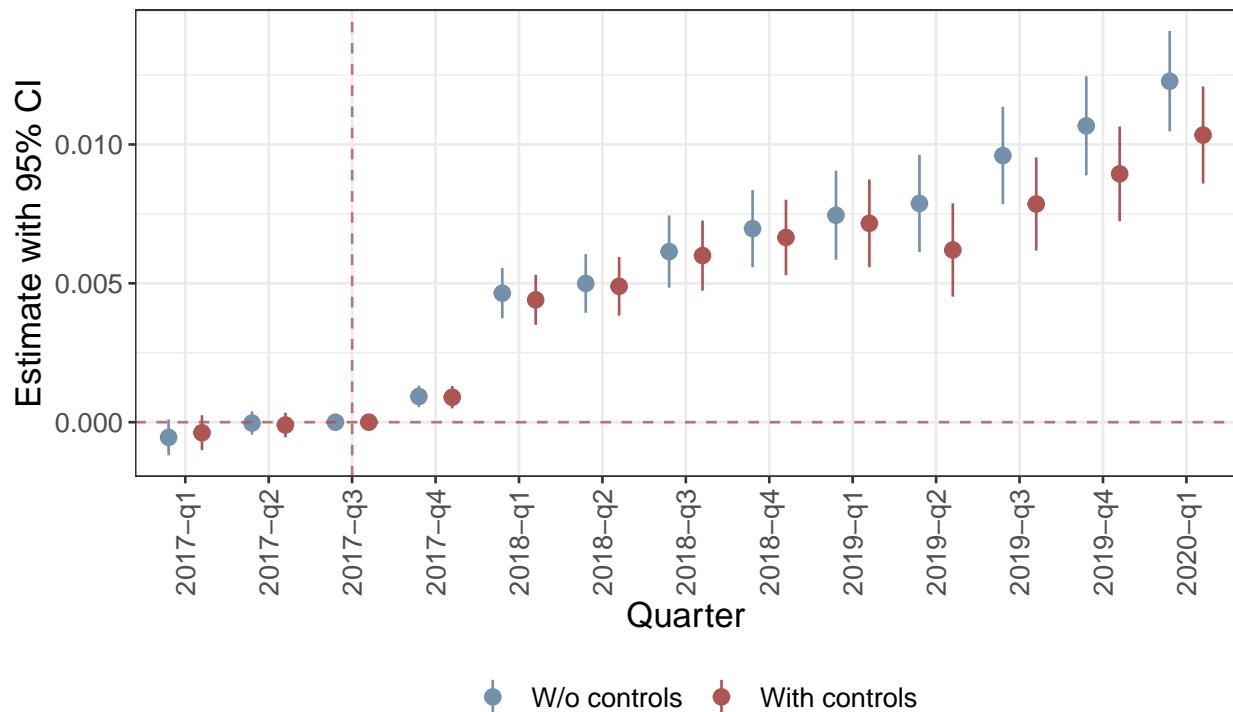
Notes: These figures are simulations using the model to show how increases in transport costs affect average profits (Panel A) and average quality (Panel B) for different value of F . When F is low, increases in transport costs lead to a larger drop in profits and quality. ([back](#))

Figure A.8: Instrument: distance from municipality to closest distribution center



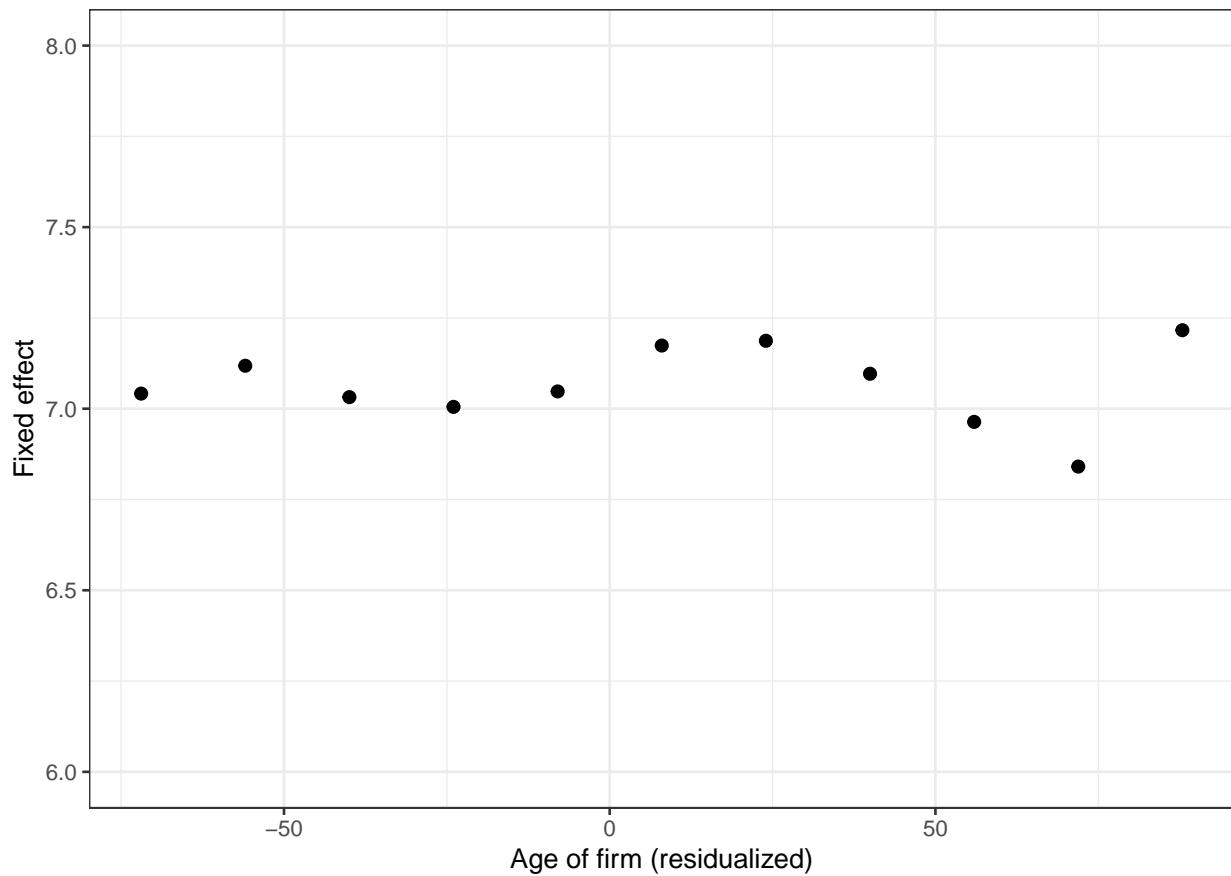
Notes: Map shows the distance in kilometers from each municipality to the closest distribution center. In order to calculate the distance, we use the coordinates of every gas station in a municipality and compute the distance to the nearest distribution center. We average over all distances within a municipality. We use INEGI's DENUE (a detailed firm directory) to locate all distribution center. WE use data from PetroIntelligence to locate all gas stations. [\(back\)](#)

Figure A.9: First Stage by quarter: gas prices



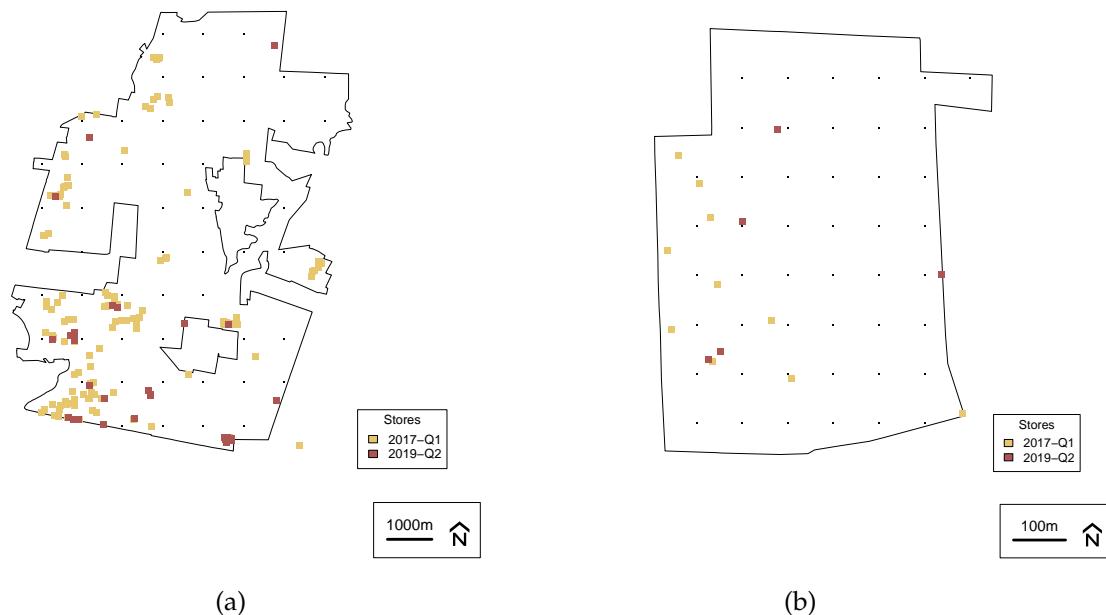
Notes: First stage coefficients of Equation 4 with and without controls. Outcome is log of gasoline price. The regression includes municipality and quarter-by-year fixed effects. Baseline municipality level controls include population, share of cars, income and a remoteness measure that is constructed as the share of people without easy access to a main road. Standard errors clustered at the municipality level. ([back](#))

Figure A.10: Binscatter plot of quality and firm's age



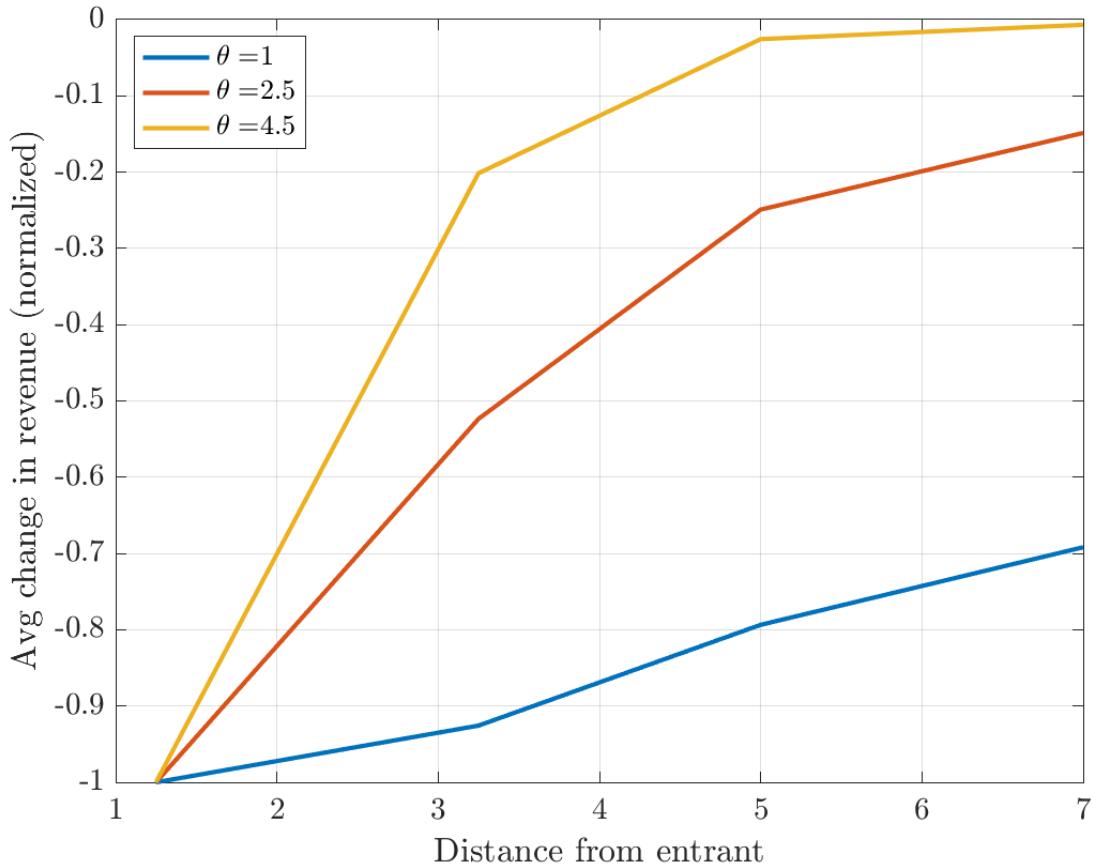
Notes: Figure shows the binscatter plot of age of firm after residualizing against the fixed effect firm-level coefficients (proxy for quality) obtained by running Equation 7. There is a flat relationship between quality and age of firm, implying that quality is not learned over time and improved. [\(back\)](#)

Figure A.11: Example of store entry effect on consumer market access



Note: This figure shows two different localities as examples of what our distance measure is capturing. We begin by randomly sampling points and computing the distance from each point (i.e. a potential household) to the closest store. We do this exercise for every period in our sample. Panel A shows entry of stores in a locality with many baseline stores while Panel B shows a locality with few baseline stores. In both panels we see how new areas are covered once new stores enter. This did not have to be the case as stores opening could have located right next to old stores. (back)

Figure A.12: Simulated Effects of Entry as a Function of θ



Note: This figure simulates the effect of a firm's entry on incumbent's sales as a function of θ . The x-axis measures the distance of the incumbent stores to the entrant. The Y-axis measures the average change in revenue for all incumbents at that distance. We normalize everything relative to the drop in revenue at the closest distance. We see that as stores are further away from entrant, their revenue decreases by less. This decay happens at a faster rate when consumers are more sensitive to transport costs (higher θ). ([back](#))

B Theoretical Derivations

B.1 Business Stealing

The effect of entry by firm $J + 1$ on a firm j is given by:

$$\begin{aligned}
\pi_j(\Omega') - \pi_j(\Omega) &= \mu (D_j(\Omega') - D_j(\Omega)) \\
&= \mu \sum_i M_i \left(\frac{\left(\gamma_j \tau_{ij}^{-1}\right)^\theta}{\sum_{j' \in \Omega'} \left(\gamma'_j \tau_{ij'}^{-1}\right)^\theta} - \frac{\left(\gamma_j \tau_{ij}^{-1}\right)^\theta}{\sum_{j' \in \Omega} \left(\gamma'_j \tau_{ij'}^{-1}\right)^\theta} \right) \\
&= \mu \sum_i M_i \left(\gamma_j \tau_{ij}^{-1} \right)^\theta \left(\frac{1}{\sum_{j' \in \Omega} \left(\gamma'_j \tau_{ij'}^{-1}\right)^\theta + \left(\gamma_{J+1} \tau_{i,J'+1}^{-1}\right)^\theta} - \frac{1}{\sum_{j' \in \Omega} \left(\gamma'_j \tau_{ij'}^{-1}\right)^\theta} \right) \\
&= \mu \sum_i M_i \left(\gamma_j \tau_{ij}^{-1} \right)^\theta \left(\frac{-\left(\gamma_{J+1} \tau_{i,J'+1}^{-1}\right)^\theta}{\left(\sum_{j' \in \Omega} \left(\gamma'_j \tau_{ij'}^{-1}\right)^\theta + \left(\gamma_{J+1} \tau_{i,J'+1}^{-1}\right)^\theta\right) \left(\sum_{j' \in \Omega} \left(\gamma'_j \tau_{ij'}^{-1}\right)^\theta\right)} \right)
\end{aligned}$$

Using the definition of consumer market access, the change in profits is given by:

$$\pi_j(\Omega') - \pi_j(\Omega) = -\mu \sum_i M_i \frac{\left(\gamma_j \tau_{ij}^{-1}\right)^\theta \left(\gamma_{J+1} \tau_{i,J'+1}^{-1}\right)^\theta}{CMA_i(\Omega') CMA_i(\Omega)} < 0$$

or using the expression for shares in equation 1 it can be written as:

$$\pi_j(\Omega') - \pi_j(\Omega) = -\sum_i s_{ij}(\Omega) \mu M_i s_{iJ+1}(\Omega') < 0$$

B.2 Welfare

In terms of consumer welfare, given an equilibrium market structure, Ω , one can show that the expected utility of consumers from i is given by:

$$\begin{aligned}
CS_i &= \mathbb{E} \left[\max_j u_{ij} \right] \\
&= \Gamma [CMA_i(\Omega)]^{1/\theta}
\end{aligned}$$

where $\Gamma \left(\frac{\theta-1}{\theta} \right)$ is a constant, and $CMA_i(\Omega)$ is the consumer market access for individuals from i . To aggregate welfare we can simply take a weighted average of consumer surplus:

$$\begin{aligned} CS(\Omega) &\equiv \sum_i \frac{M_i}{\sum_j M_j} CS_i \\ &= \Gamma \sum_i \frac{M_i}{\sum_j M_j} [CMA_i(\Omega)]^{1/\theta} \end{aligned}$$

Defining $\lambda_i \equiv \frac{M_i}{\sum_j M_j}$ as the share of individuals that live in block i , we can re-write the previous expression as:

$$CS(\Omega) = \Gamma \sum_i \lambda_i [CMA_i(\Omega)]^{1/\theta}$$

Given knowledge of θ , the distribution of fixed costs F , and amenity values γ_j , then the social planner wants to choose the market structure Ω^{SP} that maximizes consumer surplus plus net profits:

$$\Omega^{SP} \equiv \arg \max_{\Omega} CS(\Omega) + \sum_j \pi_j(\Omega)$$

What is the marginal effect on aggregate welfare of adding an extra store, i.e, going from a market structure Ω to Ω' :

$$\begin{aligned} W(\Omega') - W(\Omega) &= CS(\Omega') - CS(\Omega) + \sum_{j \in \Omega'} (\pi_j(\Omega')) - \sum_{j \in \Omega} (\pi_j(\Omega)) \\ &= CS(\Omega') - CS(\Omega) + \sum_{j \in \Omega} (\pi_j(\Omega') - \pi_j(\Omega)) + \pi_{J+1}(\Omega') \end{aligned}$$

Plugging in results from above, we get:

$$W(\Omega') - W(\Omega) = \Gamma \sum_i \lambda_i \left\{ [CMA_i(\Omega')]^{1/\theta} - [CMA_i(\Omega)]^{1/\theta} \right\} - \mu \sum_{j \in \Omega} \sum_i M_i s_{ij}(\Omega) s_{ij+1}(\Omega') + \mu \sum_i M_i s_{i,J+1}(\Omega') - F_{J+1}$$

Which can be further decomposed into:

$$W(\Omega') - W(\Omega) = \underbrace{\Gamma \sum_i \lambda_i \left\{ [CMA_i(\Omega')]^{1/\theta} - [CMA_i(\Omega)]^{1/\theta} \right\}}_{\Delta CS} - \underbrace{\mu \sum_i \sum_j M_i s_{ij+1}(\Omega') \left[s_{ij}(\Omega) - \frac{1}{\#\{\Omega\}} \right]}_{\text{Business Stealing}} - F_{J+1}$$