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

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Abstract

The retail sector in developing countries is dominated by small firms. We explain this fact with a spatial model in which high transport costs lead to small effective market sizes and, consequently, the proliferation of smaller and lower-quality firms. We show that low costs of entry are key for this result. With a new, confidential panel of firm-level data surveying the universe of mom-and-pop shops in Mexico, we test the predictions of our model. We exploit the deregulation of the Mexican gasoline market in 2017 as an exogenous shock to consumer transport costs. Where gas prices increased, the number of mom-and-pop shops differentially increased while their average size and quality fell. We provide evidence of fragmentation as the mechanism driving these effects. With our estimated model, we evaluate the welfare consequences of a licensing program that increases costs of entry for mom-and-pop shops. We show that the presence of fewer stores in the market yields a 1.4% welfare gain.

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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 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 do so. 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 developing country than in a developed one. As transport costs increase and demand becomes

[1] The 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 on traditional grocery retailers.

fragmented (and market size shrinks), only firms with low fixed costs of entry find it profitable to enter. Fixed costs of entry tend to be lower in developing countries for multiple reasons: many firms do not register to avoid paying taxes or regulatory fees; and most firms operate within their owners' house to avoid having to purchase or rent a space. If we think of fixed costs 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 observe the universe of firms in the traditional food retail sector, regardless of their formality status, since every store carries products from our upstream supplier and every household buys from

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

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

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. Once deregulation happened, each gas station set their own gasoline prices to reflect the cost of transporting gasoline plus any local factors. To promote competition and avoid high prices in areas with few gas stations, the government required each gas station to report their daily price to the market regulator.

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

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

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 with firm fixed effects and controlling for age 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.These results suggest that areas that were more affected experienced a larger quality decrease.

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 that underlie our 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 (984 feet) of the entrant, suggesting a high elasticity with respect to transport costs.

To estimate the joint distribution of quality and fixed costs, we use a method of simulated moments procedure. 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

[5] For example, this could happen if modern stores were faster at adjusting prices and passed the increase in gas prices onto consumers.

costs of entry find it profitable to open.

In the last part of the paper, we use the model to evaluate a policy in Mexico City that attempts to 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. The model yields an 8% decrease in the number of stores. Having fewer stores in the market results in a welfare gain of 1.4% due to the increase in producer surplus (less business stealing).

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 market size can impact market structure as well.

We join a 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 this paper, 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. Our data allow us to look at an entire industry that is prevalent in 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). 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).

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. We use a novel estimation strategy to estimate the key elasticity we are interested in.

Third, we speak to the literature on endogenous amenities. Previous papers have shown that demographic sorting (Guerrieri et al., 2013; Diamond, 2016); gentrification Couture et al. (2019); Hoelzlein (2020); tourism (Almagro and Domınguez-Iino, 2019; Allen et al., 2020); and slum upgrading (Harari et al., 2018) can induce endogenous responses on the amenities offered in a location. We contribute to this literature by exploring how firms endogenously respond to changes in consumer transport costs and how this entry, in turn, affects welfare.

Finally, we speak to the literature on firms in the retail sector (Bronnenberg and Ellickson, 2015; Atkin et al., 2018; Higgins, 2018; Marcos, 2022; Anderson et al., 2022; Guillouët, 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.[6]

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%.[7] 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 expiration 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.[8]

[6]Nielsen (2015) documents that 46% of all food and beverage purchases are in the traditional sector in developing countries, while this number is 1% for developed countries.

[7]Our 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%.

[8]Over 80% of firms report fixed markups (see ENAPROCE 2018).

For households, mom-and-pop shops represent a large share of expenditure on food.[9] Expenditure in the traditional food retail sector ranges from 82% in the lowest decile to 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 spatial model captures the decisions of firms of different quality levels to enter or not enter based on their market size. We show that in such a model, increases in transport costs affect market fragmentation and aggregate quality. Additionally, the model allows us to think about the different forces—namely, fixed costs of entry and the elasticity with respect to transport costs—that exacerbate the effect of transport costs and make it a policy-relevant factor for governments in developing countries. We begin by laying out the model. Then, to understand the underlying mechanisms, we describe the mapping between the transport-cost shock we observe in the data and the predictions of the model.

[9] Expenditure 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.

3.1 Model Setup

The economy consists of a city with N blocks indexed by $i, j \in \{1, ..., N\}$, 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.[10] 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.[11] Finally, we assume that on the outskirts of the city there is an exogenously 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.

3.2 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 $\epsilon_{ij} \sim Frechet(\theta)$ represents idiosyncratic factors on the basis of which a consumer who lives in i might choose to buy the good on block j.[12] Consumers in neighborhood i choose

[10] This 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.

[11] We also provide evidence for this assumption using two 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 selling at a fixed price. Moreover, Figure A.3 displays kernel estimates of the log price distribution pooled over store format and months. Log prices are expressed as deviations from a 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 (Figures A.4 and A.5, respectively, in the appendix).

[12] One can think of τ_{ij} as decreasing the effective wage people earn because it reduces the time they 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.

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:

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

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

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

3.3 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.[13] 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.[14] This store differs from mom-and-pop shops in that it has higher quality and higher fixed costs of entry. That is,

[13]We think of the quality measure as indicating a store has more variety, longer hours of operation or better customer service.

[14]We select a low-density block for the supermarket placement to capture the fact that supermarkets tend to be on the outskirts of the city, farther from where people live.

$$\gamma_k > \gamma_j, \forall j$$
$$F_k > F_j, \forall j.$$

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.[15]

3.4 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 $\pi_j \geq 0 \quad \forall j$. The equilibrium is characterized by the set of blocks that open their stores,

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

and the blocks that do not,

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

3.5 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.

3.5.1 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

[15] While we do not allow prices to differ between mom-and-pop shops and supermarkets, the quality measure is enough to capture differences between the two types of shops.

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 $\tau_{ij} \rightarrow \infty \quad$ 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 $\tau = exp(\delta_\tau * distance_{ij})$. In this way, a proportional gas price change modifies the term inside the exponential meaning that the gas shock will differentialy 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.

3.5.2 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; and (ii) the fixed costs of entry, represented by F. The first one matters because for high values of θ, even small increases in transport costs can change where consumers shop.

The second one matters because only in a scenario in which fixed costs of entry are low are firms able to enter when market sizes shrink.

While we do not take a stand on why θ differs between developed and developing countries, we do believe that low fixed costs of entry (F) are characteristic of developing countries. In our context, a few factors suggest that entry costs are low: most shops are informal and thus never have to pay government fees; upstream suppliers help provide shop owners with the necessary infrastructure to set up their shop (for example, shelves and refrigerators); and over half of all stores open on the owner's own residence, which limits how much they have to spend on real estate. Many of these characteristics generalize to other stores within the retail sector and to other countries. Given these factors, the effect of transport costs on market structure might be more significant in developing countries than developed ones.

In the appendix, we simulate the effects on entry, profits, and quality of symmetrically increasing transport costs τ for different levels of θ and F. Appendix Figures 6(a) and 6(b) show that as θ increases—that is, as consumers become more sensitive to transport costs—new firms enter sooner. And as more firms enter, average profits and average quality fall. In terms of fixed cost of entry Appendix Figures 7(a) and 7(b) show that as F falls, more shops are able to enter the market.

3.6 What Is the Effect of Entry?

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

Recall that in our model, stores differentiate themselves by the quality they offer and the block on which they enter. So consumer welfare is fully captured by market access, which depends on the stores that exist in equilibrium. If a new store enters—regardless of its quality—consumer surplus increases.[16] The closer the new store is to the consumer, the bigger the gain.

Producer surplus is given by the sum of profits of all stores in the market. An additional store that opens hurts other shop owners to the extent to which it can steal business from them. Ex ante, there is no reason to assert whether entry increases or decreases welfare. For example, imagine the extreme case in which opportunities for wage employment are

[16] Quality is not relevant since even in the case in which 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.

nonexistent such that $F_j = 0 \quad \forall j$. In this case, the social planner would want to have one store on every block to maximize consumer surplus. As soon as we move away from a setting with fixed costs of entry equal to zero, though, a trade-off arises between the variety-increasing effect (the effect of more stores in the market) and the 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 passed by Mexico's legislature in 2013, the government announced that it would stop subsidizing the price of gas, so the country moved from a national uniform price toward a price that reflected its real cost. The deregulation happened in different stages. The first change occurred in January 2017, when price bands were introduced by regions to gradually move toward a completely free market. By the third quarter of 2017, states had to eliminate all regulations and allow prices to freely fluctuate. Figure 4 shows the evolution of gasoline prices at the municipality level in our sample.

After deregulation, gas prices increased differentially across municipalities. An important part of this variation arises because logistics costs were incorporated into the price for the first time. Municipalities that were closer to distribution centers experienced less of a price hike than municipalities that were farther 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 might 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. This number increases to almost 80% of households in the highest income decile.

4.2 Data

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

Mom-and-pop shops. To examine changes in market structure, we use a monthly panel of the universe of mom-and-pop shops from 2017 to 2020. We obtained these confidential data by partnering with one of the largest upstream suppliers of mom-and-pop shops. Comparing our data with the census, we observe 1.9 stores for every store that is recorded in the census (see Appendix Figure A.2). This gives us confidence that our data set is broader than the census and includes all firms.

Apart from encompassing more firms, our data set has two important advantages over 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. Second, the data include monthly information on total input purchases (the amount each mom-and-pop shop buys from the upstream supplier), which we use as a proxy for sales. Census data, while covering a wider range of variables, are only available every five years, making it impossible to study short-term effects of micro shocks.

Two data issues are that we do not observe sales to final consumers and cannot observe total sales of all available products. The first concern is mitigated by the fact that products from our supplier have relatively short shelf lives and representatives of the supplier exchange old products with new ones to guarantee freshness. This implies that input purchases by the mom-and-pop shop closely follow sales to the final consumer.[17] As for the second concern, we assume that sales of other brands follow a similar pattern to that in our data. This is not an extreme assumption, since sales of products purchased from our supplier represent around 20% of total sales and include different brands and product types.

Because the data do not include a variable for opening and closing dates, we define entry and exit in two ways and show that our results are robust to both. The first definition uses each store ID as a distinct store, the store's first appearance in the market as its entry date, and its last appearance as its exit data.[18] Under this definition, a store can have periods of inactivity in which 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, it 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

[17]We do not worry about stores' ability to manage inventory and potential discrepancies that could arise because stores buy products that they cannot sell. This is because the upstream supplier is responsible for keeping track of inventories. In every store visit, a representative from the supplier examines all unsold products and exchanges any that are close to their expiration date. Because the representatives are paid according to their sales net of any exchanged products, they have strong incentives to ensure store owners are not overbuying products. Although the frequency of the visits varies from daily to biweekly depending on the stores' size, the representatives always visit without requiring any effort from the store owners.

[18]We consider stores that are present in the first period as incumbent firms.

definition, we observe high turnover. 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%.[19]

Finally, our data set also contains information on whether the shop has a tax ID, the gender of the store owner, and the number of establishments each firm owns. Table 1 shows summary statistics. Mom-and-pop shops are mostly informal (83% of them do not have a tax ID), 62% are owned and operated by women, and the vast majority are single-establishment firms. Mom-and-pop shops sell on average $223 worth of products from our data provider every month, and each item costs around half a dollar.

Household expenditure. To look at households' expenditure patterns, we use Mexico's survey of household income and expenditure (ENIGH). This survey is publicly available from INEGI. Because the deregulation happened in the last quarter of 2017, we use three waves of the survey—2016, 2018, and 2020—which contain information on close to 100,000 households. The survey includes comprehensive income and expenditure data; importantly, because people report in a diary what they buy and where they buy it, we can see the type of store where each good was purchased. Thus, we are able to see consumption both at mom-and-pop shops and 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, package-size, and variety level (for example, diet Coca-Cola in 600 ml bottles) for a number of products at different establishments. Importantly, the confidential data set includes information on the municipality where the price was recorded and the type of establishment (that is, traditional or modern). This is relevant because we can see generalized price changes as well as heterogeneity between traditional and modern stores following the municipality-level shock. The final data set contains 2.7 million store-price observations over the 2016–20 period.

Gasoline price. To measure gas price changes, we obtained daily data on prices at the gas pump at every gas station in the country. As part of the Energy Reform, every gas station is required to report its prices every day; the data are published daily by Mexico's Energy Regulatory Commission with information on the name of the gas station, its

[19] Our 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%.

address, the type of fuel (gasoline or diesel), the octane rating, 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 set 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 cover the 2017–20 period.

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 are 28 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 compute their average. 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 far they are willing to go in order to shop. These effects in turn can have effects on which firms enter (or exit) the market and on their size. We use the deregulation of the gasoline market in the last quarter of 2017 as an exogenous shock that increased consumer transport costs. As part of the Energy Reform, Mexico moved from a nationally 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 in which gas prices increased to municipalities that suffered less of price hike.

To ease endogeneity concerns stemming from the possible correlation between gas prices and local economic conditions, which also affect market structure, we instrument gas prices with distance from each municipality to the nearest gasoline distribution center. The idea is that once prices were able to fluctuate, municipalities with higher logistics costs 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 refineries, ports, and entry points at the Mexico-US border. In total, there are 28 distribution centers. We obtain their locations using DENUE and measure the linear distance from every gas station to the closest gasoline distribution center. For each municipality, we take the average of all gasoline station distances. Appendix Figure A.8 depicts the distances from every municipality to its closest distribution center.

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

$$log(gasPrice_{mt}) = \alpha_m + \delta_t + \beta \log(distDistrCntr_m) \times Post_t + \mathbf{\Gamma} \boldsymbol{X}_{m0} + \epsilon_{mt} \tag{3}$$

Here, m represents a municipality and t represents a quarter. We include municipality and time fixed effects; $\boldsymbol{X_{m0}}$ are a set of baseline municipality-level control variables. Our coefficient of interest is β, which captures the effect of being farther from a distribution center on gasoline prices after deregulation.

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

$$Y_{mt} = \alpha_m + \delta_t + \sum_k \beta_k (log(distDistrCntr)_m \times \mathbb{1}[t = k]) + \boldsymbol{\gamma}_0 \boldsymbol{X}_{m0} + \epsilon_{mt} \tag{4}$$

Here, 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 farther from gasoline distribution centers at different times.

IV specification. Because deregulation happened in a somewhat-staggered fashion—with a minority of states and one municipality deregulating prices before all other jurisdictions—we exclude the first movers from the analysis. Our final data set contains 2,333 municipalities in 29 states. Our main equation of interest is the following second-stage equation:

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

We instrument $\widehat{gasPrice}_{mt}$ with Equation 3.

We now revisit the identifying assumptions in our estimation strategy. To start, our identification strategy must satisfy the two main IV assumptions. Relevance requires that municipalities that are farther 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, distance to distribution centers must only impact market structure via changes in consumer transport costs. One might worry that being far from a distribution center is correlated with other characteristics that impact market structure. This concern is 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—population count, 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 see no relevant changes in our point estimates.

Finally, we recognize that distribution centers are unlikely to have positioned themselves randomly, but it is hard to imagine that 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 custom offices between the US-Mexico border (the last refinery was built 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 to use our instrument. In Section 6.2 we present our main results, which concern how transport costs affect market structure. In Section 6.3 we zoom in on the firms that are entering the market and characterize the selection effect. Next, in Section 6.4 we provide evidence for our mechanism. We show that household mobility is in fact affected by the gasoline shock and that shopping patterns change. Last, in Section 6.5 we run robustness checks for other potential confounding factors and find no evidence of them.

6.1 First Stage

We start by documenting the first-stage relationship: do municipalities that are farther 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 2 periods before the policy change and 10 periods after, where each period represents a quarter. Gas prices in the periods before deregulation did not differ by a municipality's distance to a distribution center (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's 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 0.06% 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 farthest 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 panel of mom-and-pop shops contains data from 2017 to 2020. We exclude observations after the first quarter of 2020 to avoid including the beginning of the COVID-19 pandemic, during which mobility was highly impacted and the service sector severely restricted. Turning to outcomes, we begin by showing reduced-form effects of being farther from gasoline distribution centers. In particular, we ask: how does distance to distribution centers impact the number of mom-and-pop shops and their size? Figure 9 shows the reduced-form event-study effect on number of stores in a municipality. We see that before deregulation, there were no systematic differences between municipalities. After the policy change, the number of stores in treated municipalities increased relative to untreated ones. The effect was small at first but increased one year after the deregulation.

The delay in store openings (relative to the date when gas prices increased) is likely because prospective store owners had to adapt their space and establish contact with upstream suppliers to stock their store. It might also be explained by a delay in consumers' responses regarding where to shop.

For the magnitude of the effect on 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 relative to the baseline mean.

To further understand what is driving the increase of stores, we look at entry and exit. Our model predicts that following an increase in consumer transport costs, new stores enter to satisfy the newly fragmented markets. Thu, empirically, we 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 some municipality-quarter pairs don't haven any openings or closings, 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 does explain our results. There is a 13.5% increase in entry, and, while exit is also decreasing, the coefficient is much smaller (-0.73) and not significant.

Now 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 expect to see a significant increase in aggregate sales at mom-and-pop shops; but if the second effect dominates, demand at mom-and-pop shops will not increase since people are simply switching store locations but not 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 is deregulated, we see a slight drop in aggregate sales in affected municipalities in the first three quarters, 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 increase in total sales. While the effect is positive, the coefficient is not significant.

If the only mechanism operating was substitution from supermarkets to mom-and-pop shops, aggregate sales would unambiguously increase. Because that is not what we observe, we interpret the large standard errors as an indication that both mechanisms are operating. In some areas, demand is increasing because there is in fact substitution from supermarkets, but in other areas demand is flat with a change only for the specific stores at which people shop. The model gives us a specific microprediction that we can test: aggregate sales at mom-and-pop shops should take an inverse U shape with respect to distance to the closest supermarket.

We test the prediction by identifying the pre-deregulation location of all supermarkets in the country using the national registry of firms (DENUE) and calculate the distance from a municipality's centroid to the closest supermarket. The first three columns of Table 4 show the effect on mom-and-pop shops' aggregate sales at different terciles of distance. The largest effect is concentrated in the middle 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 km to reach one. For those far from a supermarket (T3), we see no substitution effect since most likely nobody was traveling to one anyway (on average they would have had 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 in the first and thrid tercile are significantly different from the coefficient in the second tercile (Columns 4–6 of Table 4). That we see a significant and large increase in the number of stores for both the bottom and top tercile indicates that our results are not completely driven by a substitution effect from supermarkets to mom-and-pop shops. Panel B of Table 2 confirms that the same patterns that we observe using the full sample are present when we restrict the sample to municipalities without a supermarket. We provide further evidence that both mechanisms are operating when we examine outcomes using the household-expenditure survey.[20]

Our third outcome regarding market structure is the average size of a firm (as measured by average sales) in places that are farther from distribution centers relative to those that are closer. Figure 11(a) shows the reduced-form quarter-by-quarter coefficients of Equation 4 with average sales at mom-and-pop shops as the regressand. We observe a reduction in the size of firms in more intensely treated 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 close to $15. Recall that the sales we are able to see are only a fraction of total sales. If we assume that sales of other goods follow a similar pattern and that our data provider represents around one-fifth of all sales, then sales decrease by $75 in each store.

To understand whether stores entering are stealing business from incumbents or whether entrants are very small and thus mechanically cause average size to fall, we look at average sales with a sample restricted to firms that were operating in the first quarter

[20]Equally as important, over 65% of municipalities do not have access to a supermarket so it's unlikely that all of our effect is explained fully by the substitution channel.

of 2017 (that is, the first period available in our data). If entering firms fully explain the drop in average size, then we 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 we used the full sample); their drop is 75% of the total drop in average sales. Thus, 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 by the number of mom-and-pop shops 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 fewer mom-and-pop shops should see larger effects on average sales than those where more stores exist at baseline. We also expect fewer shops to enter in municipalities with thick markets. In order to test this conjecture, we run the same IV specification as Equation 5 and add an interaction term in the following way:

$$\begin{aligned} Y_{mt} =& \alpha_m + \delta_t + \beta(log(\widehat{gasPrice}_{mt}) \times Post_t) + \\ & \sum_q \rho_q \left(M\&P\mathbb{1}(quintile = q)_m \times log(\widehat{gasPrice}_{mt}) \times Post_t \right) + \gamma_0 \boldsymbol{X}_{m0} + \epsilon_{mt} \end{aligned} \tag{6}$$

The coefficients of interest are ρ_q, which indicate how the outcome variable is impacted in municipalities in different quintiles of the baseline distribution of mom-and-pop shops. In Table 5 we show the results by quintile. A clear pattern emerges: as markets become thicker, fewer stores enter and the business-stealing effect shrinks. These results imply that the effects are mostly concentrated in municipalities with fewer 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 enter the market are those with low fixed costs of entry. This is because only these shops find it profitable to operate with few consumers. These two facts taken together imply that the stores that enter the market are lower quality and have low fixed costs of entry.

Quality. To empirically examine how average quality changed after the shock to transport costs, we need a firm-level quality measure. While our data set 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:

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

Here, j is 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 accounts for the possibility that older stores sell more than newer stores. γ_j captures the remaining shop-level variation. Because markups are fixed and prices vary little, we interpret these coefficients as all the nonprice productivity differences between firms; this includes hours of operation, cleanliness, and customer service. We use the coefficients to construct a municipality-quarter-level quality measure, whose variation comes from the change in composition of the set of operating firms within a municipality.

Figure 12 plots the quarter-by-quarter coefficients of Equation 4, in which the outcome is the average value of operating firms' quality (coefficients γ_j come 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 0.2 standard deviations. To ensure the effect is not mechanical, we check whether quality is static or whether store owners learn to improve it. We use pre-treatment data and look at the correlation between quality (as measured by γ_j) and firm age. If quality changed over time, then older firms should 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. In Appendix B, using proxies for fixed costs of entry, we show that entrants in municipalities that were farther away from gasoline distribution centers have lower fixed costs than those in closer municipalities.

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 mom-and-pop shops instead of supermarkets) and a fragmentation channel within the shops sector (changing which shops people patronize). Here we provide further evidence

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

that both effects are present.

Substitution away from supermarkets. As gas prices increased, did people substitute away from supermarkets and toward 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. It asks 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 shop. Our final data set covers 1,460 municipalities and over 200,000 households. Because we only have three periods, we cannot conduct event studies, but we can directly estimate a modified version of Equation 5:

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

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

Being exposed to a higher gas price after deregulation leads to a decrease in the likelihood of shopping at supermarkets and a slight increase in the likelihood of shopping at mom-and-pop shops. While the coefficients are not significant, the signs of the effects are as expected. The modest increase in number of households reporting that they are shopping at a mom-and-pop shop is likely because most people reported already buying at least one item at this type of store, as reflected in 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, and monthly. We group these answers into high-frequency shopping (daily and biweekly) and low-frequency shopping (weekly, every two weeks, and monthly) and report coefficients in Columns 3 and 4 of Table 6. A similar pattern emerges—more households report shopping at high frequencies and fewer report buying at low frequencies—suggesting that people are shopping more at mom-and-pop shops.

Last, 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 at mom-and-pop shops and 0.4% less at supermarkets.

Substitution within the shop sector. The mechanism behind gas prices' substitution effect concerns how people commute within a city. To look at whether gas price increases modified households' commuting behavior, we again use data from INEGI's Income and Expenditure Survey, this time looking 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 the value of 1 if the household reported expenditure in that category (Column 1 reports results for gasoline and Column 2 for public transportation) and 0 otherwise. For a 1% increase in the price of gasoline there is a 0.23 percentage-point decrease in the number of households purchasing any gas and a 0.48 percentage-point increase in the number using public transportation.

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

With ideal data, the next exercise would be to see how gas price increases affect which mom-and-pop shops households shop at. We expect that following the gas price shock, households switch to shops closer to them. While no data on the matter exist, we can overcome this challenge thanks to the granularity of the data we do have. Within each municipality, we uniformly sample 1,000 random points and compute the distance between each point and its closest store for every quarter. With that information we construct a municipality-quarter measure of average time traveled to capture how far 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 (which represent potential households) in gray, incumbents in blue, and entrants in red. We calculate the distance from every gray point 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 served.

Figure 13 shows coefficients from Equation 4; we see a decrease in average distance traveled. The results imply that new stores are not simply opening in the same places as old stores. This is important because mom-and-pop shops tend to locate on the same street as one another. IV estimates shown in Table 7, Column 5 tell us the magnitude of the effect. For a 1% increase in gas prices, average distance traveled decreased by 1.87%, or close to 90 meters. If we consider the 5% increase in gas prices in municipalities farthest from distribution centers, this implies that distance traveled falls 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 on each round trip, shoppers walk close to a kilometer less than before.

6.5 Robustness

Real wages. An alternative mechanism that could explain our results is wages falling in places where gas prices go up. When households face a reduction in income, they have a stronger incentive to open a mom-and-pop shop as a side business to supplement their income. The possibility of opening a mom-and-pop shop to supplement income seems unlikely since 92% of owners report operating their 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 (excluding gas prices) separately to determine the extent to which real wages changed. To explore this possibility, we begin by using the microdata on prices that INEGI uses to construct the CPI. One feature of the price data is that they not only track prices of goods but also prices of services like health care, education, and rent. The confidential data include the municipality in which the price was recorded, which we use to verify that prices did not change differentially after the gas price shock.

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

$$log(price)_{gst} = \eta_{gs} + \delta_t + \sum_k \phi_k Treated^k_{m(s)t} + \epsilon_{gst} \tag{9}$$

Here, g is a barcode-equivalent product, s is the store at which the price was recorded, and t is the quarter. We average the price data at the quarter level to match the periods we use for our main analysis. We include product-by-store and quarter fixed effects. Figure 14(a) shows that all coefficients are statistically insignificant both before and after the gas price shock.

Next, we look at wage effects using publicly available social security data. Figure 14(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 farther from gasoline distribution centers and hence experienced a greater gas price increase. These two figures taken together rule out large real-wage effects making it unlikely to be the mechanism behind our results.

Employment. A second possible alternative mechanism concerns changes in employment opportunities. It could be that firms cannot adjust on the wage margin but instead adjust total employment. If the unemployment level increases in areas in which gas prices increase, then the rise in number of mom-and-pop shops could be explained by a decline in outside options for potential shop-owners.

To look at employment changes, we again use publicly available social security data, which track all employment in the formal sector. Figure 15 shows reduced-form coefficients for the evolution of employment. There is no decline in employment. On the contrary, there appears to be a insignificant and small increase in employment in municipalities that are farther 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, after the gas price shock, they increased the price of their goods. This in turn could lead (price sensitive) consumers to switch their shopping location.

To empirically test this, we again use INEGI's price data. We estimate Equation 9 separately for modern stores (that is, supermarkets) and traditional stores, exploiting the fact that enumerators report the type of store at which the price was recorded. Figure 16(a) shows the evolution of prices in modern stores, and Figure 16(b) traditional stores. For both types of store we see no price changes, ruling out the possibility that prices are driving 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). 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. And surveys conducted by INEGI reveal that less than 5% of the shops' expenses correspond to gasoline. Upstream suppliers, in contrast, could have been affected by increases in the gas price. But if this were the case, we would expect the sign of the results to go in the opposite direction of what we find. That is, if upstream suppliers wanted to reduce their gasoline expenditure because prices increased, we would expect to see less store entry (not more), especially since it appears that the size of the market (as measured by aggregate sales) is not growing.

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 onto incumbents once new firms enter. In Section 7.3 we estimate the parameters of the joint distribution of quality and fixed costs of entry (μ_F, μ_γ, σ_F, σ_γ, and $\rho_{F,\gamma}$).

7.1 Data and Equilibrium

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

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

Travel times are calculated using linear distances between every 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; Tsivanidis, 2019; Zárate, 2019), we parameterize commuting costs using the following expression:

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

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

Last, we set the markup at 20% of total sales in accordance with reports from the National Alliance of Small Businesses (ANPEC) on how much these stores earn.

Equilibrium. Having a discrete-entry model is challenging because of the discrete jumps that occur 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.[22] Importantly, our algorithm uses the highest possible level of 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 (the number of blocks in the city), which indicates whether a firm on block j is open or closed. Then, in every iteration, the algorithm first evaluates whether $\mathbf{y}$ is an equilibrium by calculating the profits of the firms that open and the profits of each of the closed firms. Finally, it opens the closed firms (one by one) and calculates the new profit distribution. If the opened firms earn positive profits and the closed firms negative profits, then the algorithm terminates and generates $\mathbf{y}$. Otherwise, from the set of all the closed firms 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 them earn negative profits, then it closes the one with the smallest value. 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 returns to the evaluation step and iterates until it finds an equilibrium.

More concretely, 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 find depends on the initial $\mathbf{y}$ vector.

[22] Other papers that deal with discrete-entry models use similar methods to find an equilibrium with explicit selection rules—for example, Aguirregabiria and Vicentini (2016); Jia (2008); Matsuyama and Ushchev (2020).

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 matters because it tells us how sensitive people are to changes in transport costs and quality.

Estimating θ typically relies on detailed data on consumer shopping behavior, which is hard to obtain in developing countries, especially for the type of informal firm we study in this paper. To overcome this challenge, we propose a novel estimation strategy that uses indirect inference and exploits 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 of the model, suppose we start from an equilibrium in which the first $J' < J$ firms open: $\Omega \equiv \{1, ..., J'\}$. This determines the profits of the firms that are currently in the market so that we can index profits of any operating profit by the set of other operating firms:

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

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

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

The decrease in profits for a firm on block j from the entry of a firm on block $J+1$ is a weighted average across all blocks of the markup times the initial share of all of firm j's sales to 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 C.1.

Crucially, the spatial decay of the business-stealing effect depends on the magnitude of θ. To show this point, we simulate the effect of entry of a new store on incumbent stores for different values of θ. Appendix Figure A.12 shows the results; we can see that for higher values of θ, only firms that are close to the entrant are affected, while firms farther away do not see a change in their revenue.

Leveraging our fine-grained geographic panel data, we can conduct 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 set and identify all entering firms.[23] The question we answer is: what happens to incumbents' sales when a new firm enters? We construct various rings in increments of 300 meters around every store entry in order to measure the spatial decay.[24] We conduct an event study in which event time is normalized to one period before entry and compare the effect of entry on incumbents' sales. We interact event-month dummies with 300 meter rings and up to 1200 meters, indicating the distance from each incumbent store to the associated new store (treated ring). Incumbents located between 900 and 1200 meters from a new store represent the omitted group and serve as our control. We estimate the following event-study equation at the level of the incumbent shop j, entrant e, and month t:

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

Here, j is an incumbent store in municipality m in month t and $r(j,e)$ is the ring r where j is located in relation to entrant e. $\beta_{\tau,r}$ is the coefficient of interest; it captures the evolution of sales of incumbent firms in each treated ring in relation to the outermost ring. The entry-date fixed effects ($\alpha_{e,t}$) flexibly account for time patterns across all rings around each new store e. Entry-ring-municipality fixed effects ($\kappa_{e,r(j,e),m(j)}$) control for baseline differences of incumbents in each ring. Figure 17 shows the results. When a new store enters, only the stores at a 300 meter distance see a decrease in sales, suggesting fast spatial decay and thus a large θ. That consumers are so sensitive to transport costs and are willing to change where they shop even for small distances implies that a store's entry has important localized spillover effects that dissipate quickly with distance.

We 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 Bogotá, the commuting elasticity is 3.398. Not surprisingly, our estimated elasticity is larger than in

[23]This exercise is independent from what we do in Section 5. Here we are interested in understanding the effect of entry regardless of the gas price shock.

[24]As a robustness check, we try the exercise with different-sized rings and find that at the 300-meter mark, sales of incumbents stop being affected by the opening of a new mom-and-pop shop.

the previous studies since our context is also different. Both referenced papers examine commuting elasticities for job choice, while we explore a context in which people are buying a homogeneous product (same product quality and same price) with inelastic demand.

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 lognormal 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 data describe the mean and standard deviation 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.

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

8 The Welfare Effects of High Transport Costs

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

Market structure under different levels of transport costs and fixed costs of entry. We started our paper 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 together with low fixed cost of entry contribute to this difference. Evidence from Akbar et al. (2022) suggests that developing countries have in fact higher transport costs. And as we discussed, the lack of regulation of these retail stores, the poor outside options for store owners, and the small investment they have to make to open a store all suggest that fixed costs are low (and lower than in developed countries).

To understand the extent to which transport costs and fixed costs of entry explain 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 costs of entry and finally modifying both at the same time. For our counterfactual exercise, we use transport costs and fixed costs of entry 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 midpoint. 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 in the US. In the least conservative case, we would see 41% fewer stores.

	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

8.1 Welfare and Efficiency

In order to find welfare effects and efficiency properties, we derive expressions for consumer surplus and producer surplus. We then use these expressions and our estimated model to examine 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 as follows:

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

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

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

In order to derive the expression for aggregate welfare, we take the weighted average of consumer surplus and define $\lambda_i \equiv \frac{M_i}{\sum\limits_j M_j}$ as the share of individuals that live on block i such that

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

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 people have to travel and how much they have to pay in transport costs) and the quality of stores.

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

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

Here, Ω is the set of operating firms. We exclude from our welfare calculation the profits of the supermarket because the planner does not care about the profits of supermarkets. The supermarket still matters because, from the consumer side, its existence increases consumer market access and, from the producer side, how many people choose to go to the supermarket relative to the mom-and-pop shops determines profits.

Is there excess entry? Nothing in the model tells us whether there is too much entry, but there is a trade-off every time a new store enters. Consumer surplus increases because consumers prefer 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 see this more clearly, we can look at the marginal effect on aggregate welfare of adding an extra store—that is, going from market structure Ω to Ω':

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

In Appendix C.2 we show that plugging in values for consumer surplus and profits we derive the following:

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

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 steal from incumbents and the additional fixed costs that are 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.[25] The program targets small stores and asks their owners to pay a small fee and 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, and more). 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 license and scale it by the mean wage. We see this number as the lower bound of the cost imposed by the program.[26]

In Figure 18 we show the welfare effects of imposing higher costs of entry. We assume

[25] More information on the program can be found here.

[26] This is because there are many other requirements to obtain the license, such as showing documentation that shop owners might not have and would need to pay an additional cost to obtain.

that the government rebates the tax to households. We compare welfare changes to the baseline case of no licensing costs. Note first that making mom-and-pop shops pay for a license to operate decreases entry and increases welfare by 1.4% relative to the baseline case. Second, the baseline equilibrium (licensing cost of zero) is not far from the maximum welfare point. This is important because if the nonmonetary costs of obtaining a license are high enough, then welfare decreases.

Our results suggest there is some scope for welfare gains by modestly decreasing the number of stores in the market. This result should be taken with caution since our model is restrictive in many ways: it assumes full information on the part of 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

Small firms are prevalent in developing countries. This paper established how transport costs and low fixed costs of entry can be important factors for understanding this market structure. Exploiting a novel confidential panel of firm-level data and a shock to consumer transport costs, we provided micro-evidence that increases in transport costs result in more store entry and, consequently, smaller-sized stores (because of business stealing) and lower-quality mom-and-pop shops.

Using household-level survey data, we provided evidence that two mechanisms are at play. First, we documented that households substitute away from supermarkets and toward mom-and-pop shops. Second, we found a meaningful decline in households' gasoline consumption and a parallel increase in public transportation usage. This reduction in mobility within a city affected consumers' choice of where to shop and led to substitution among mom-and-pop shops.

We then estimated the relevant parameters of the model. We uncovered high elasticities with respect to transport costs, implying that markets are very localized and that store entries have large business-stealing effects. The model laid out provided a clear trade off between consumer's love of variety from having more stores in the market and a business stealing effect from each new store.

The counterfactual exercise of introducing a licensing program that limits the number of shops in the market suggests there are potential efficiency gains from having less shops. Nonetheless, even at the optimal licensing cost, welfare would increase by 2% at most which suggests that the observed equilibrium is not far from the social optimum.

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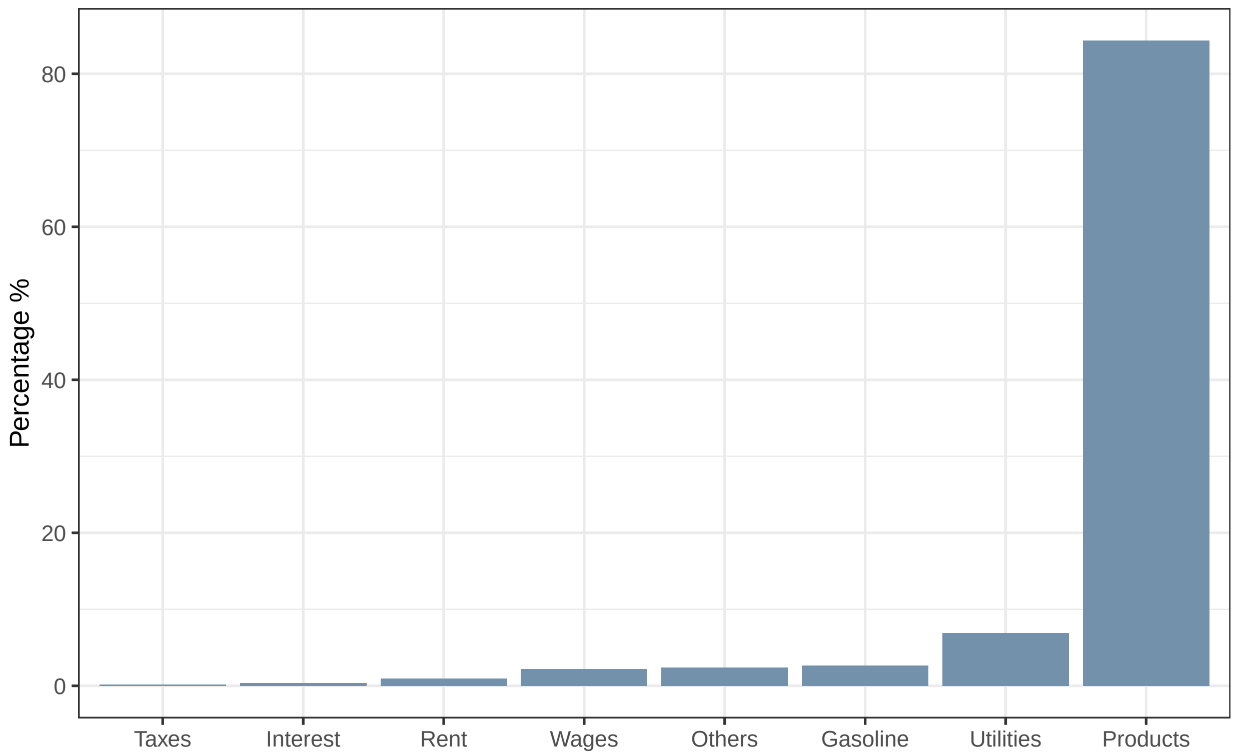
Figures

Figure 1: Typical medium-sized mom-and-pop shop

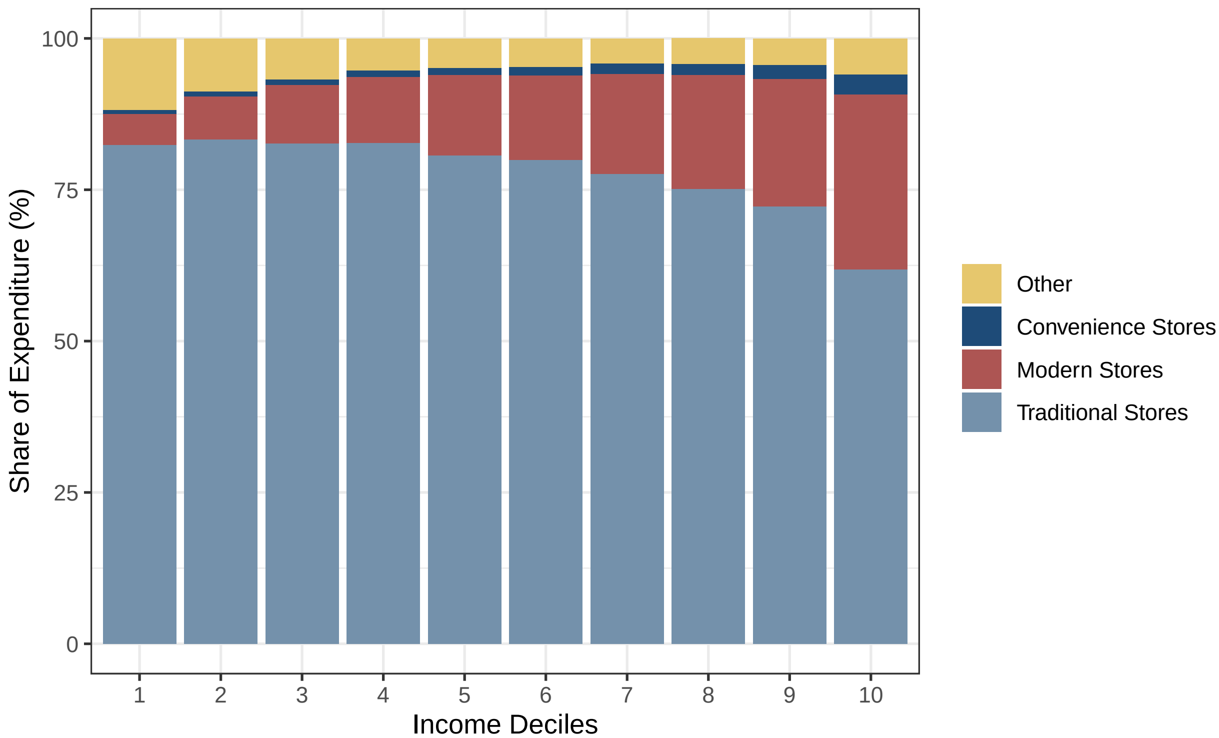
Notes: This figure was taken from Google Maps' street view and shows a medium-sized mom-and-pop shop in Mexico City. As is typical of other stores, the store is part of a house (note the garage door on the left-hand side). Note that the majority of the infrastructure comes from upstream suppliers (the posters, the refrigerator, and even the store awning). (back)

Figure 2: Expenses of mom-and-pop shops



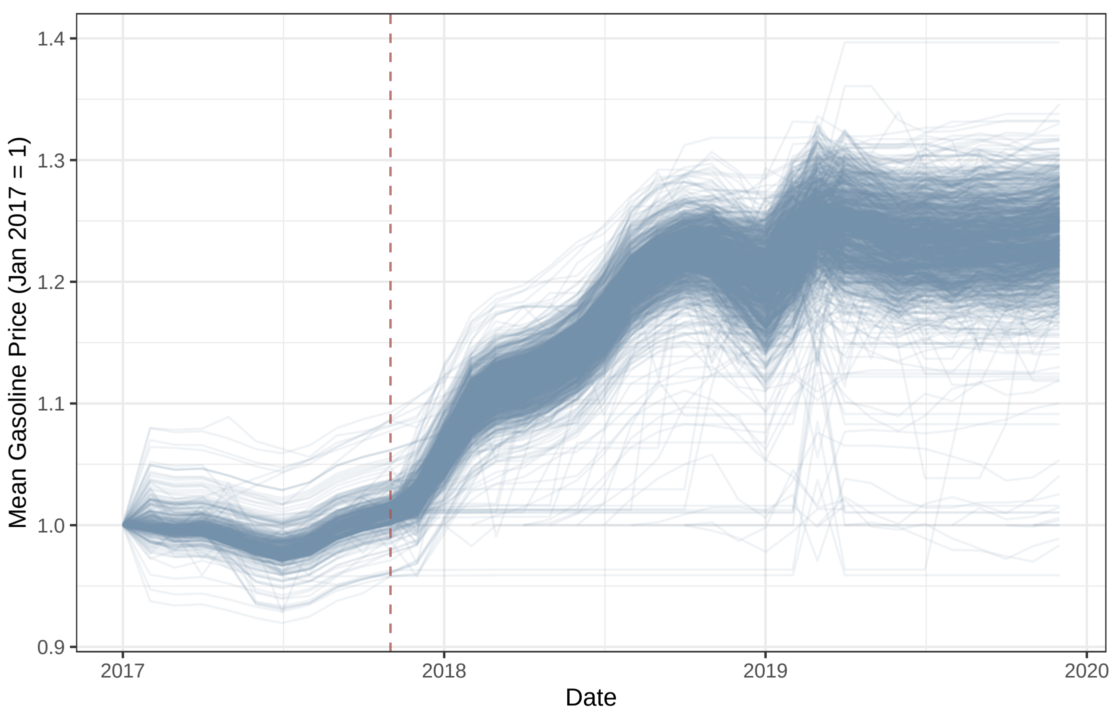
Notes: This figure uses data from INEGI's 2020 Income and Expenditure Survey (ENIGH), which asks business owners how much they spend on different expenses. We filter the data to only include owners of mom-and-pop shops ($N = 10,918$). Over 80% of expenses correspond to buying products to resell. (back)

Figure 3: Food expenditure by decile



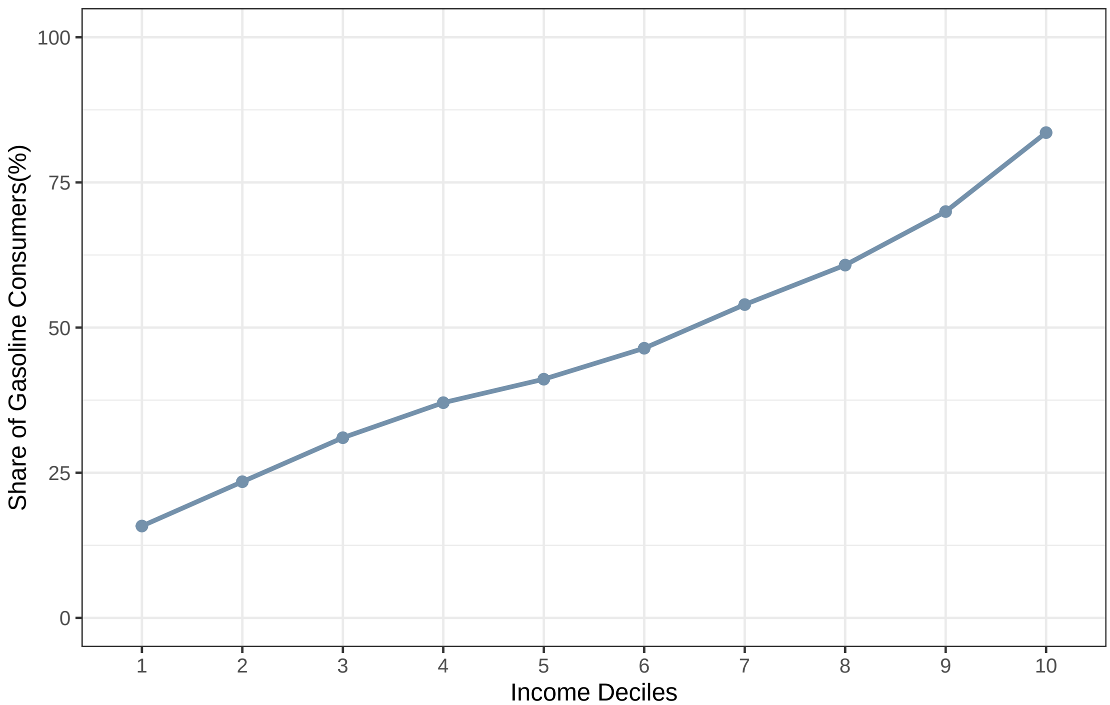
Notes: This figure uses data from INEGI's 2018 Income and Expenditure Survey (ENIGH). The survey asks households where they purchase their food and household goods. Traditional stores include mom-and-pop shops (57%), street vendors (22%), and speciality shops (21%), which include tortilla shops and meat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

Figure 4: Raw trend of gasoline prices at municipality level



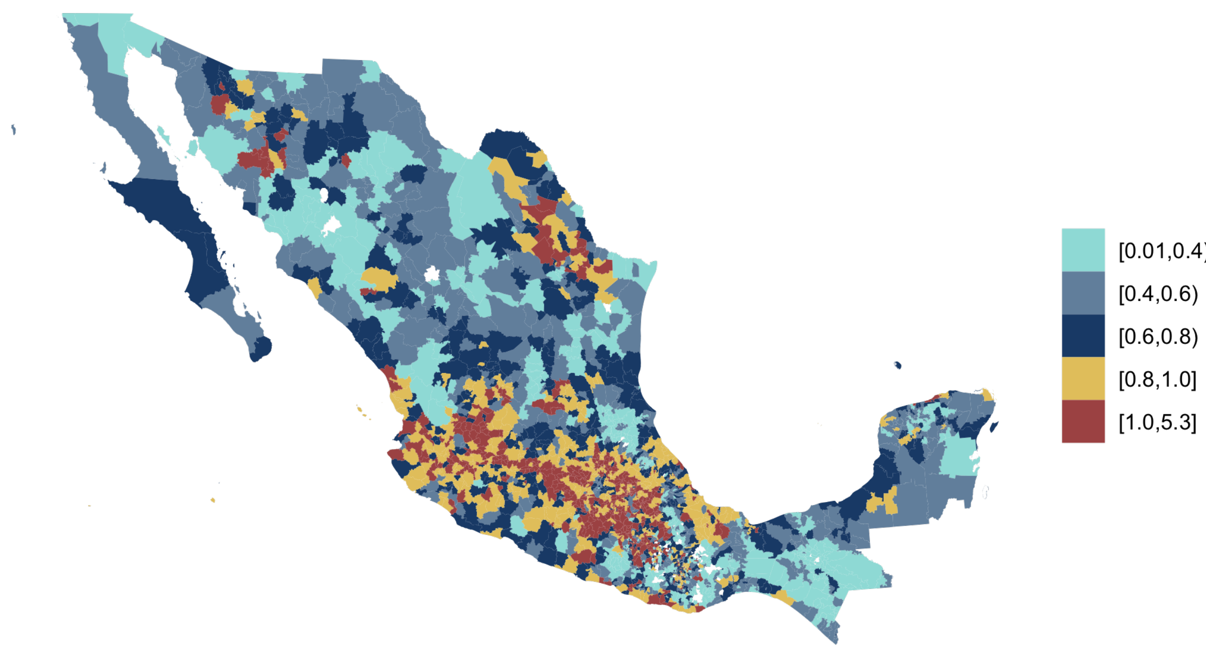
Notes: This figure shows the raw trend of gasoline prices. Each line represents a municipality. Prices are normalized to January 2017 prices. The red dotted line represents the date when prices where allowed to fluctuate. Data employed are daily gas-pump-level information obtained from PetroIntelligence.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

Figure 5: Gasoline expenditure by income decile



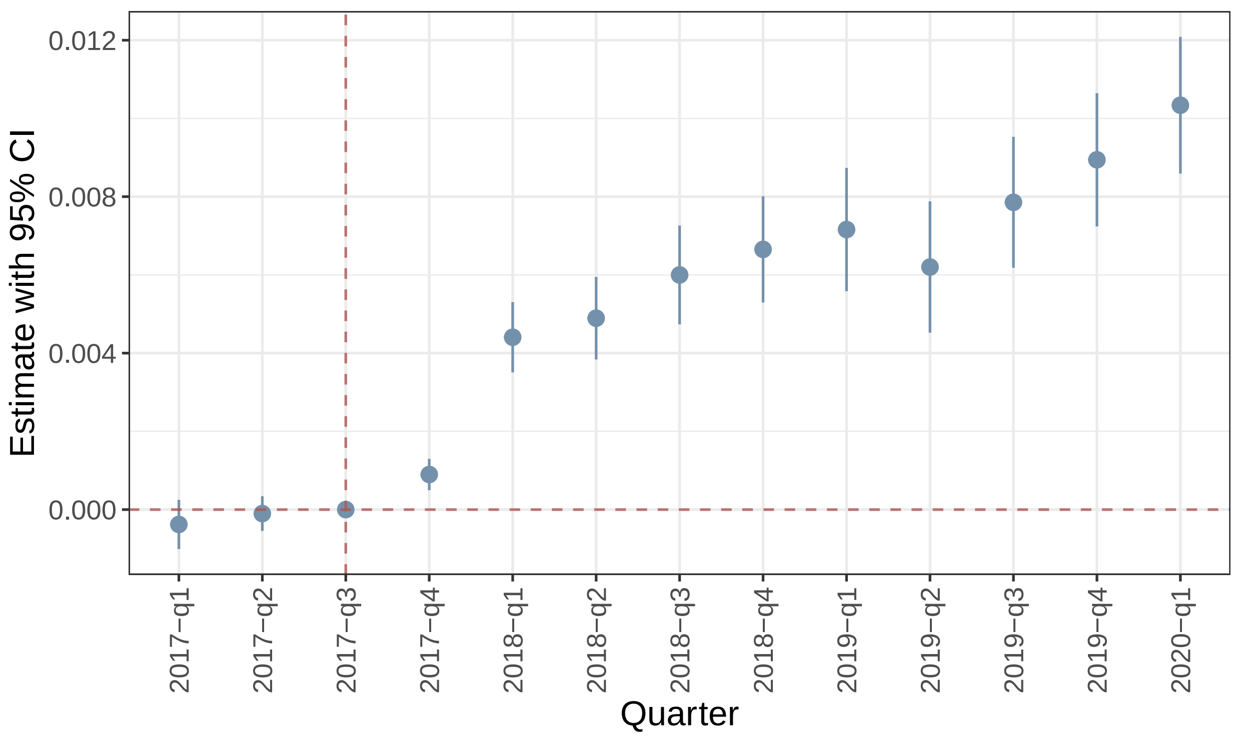
Notes: This figure shows the percentage of households by decile who report gasoline expenditure. To construct the figure we use data from INEGI's Household Income and Expenditure Survey (ENIGH). (back)

Figure 6: Density of stores



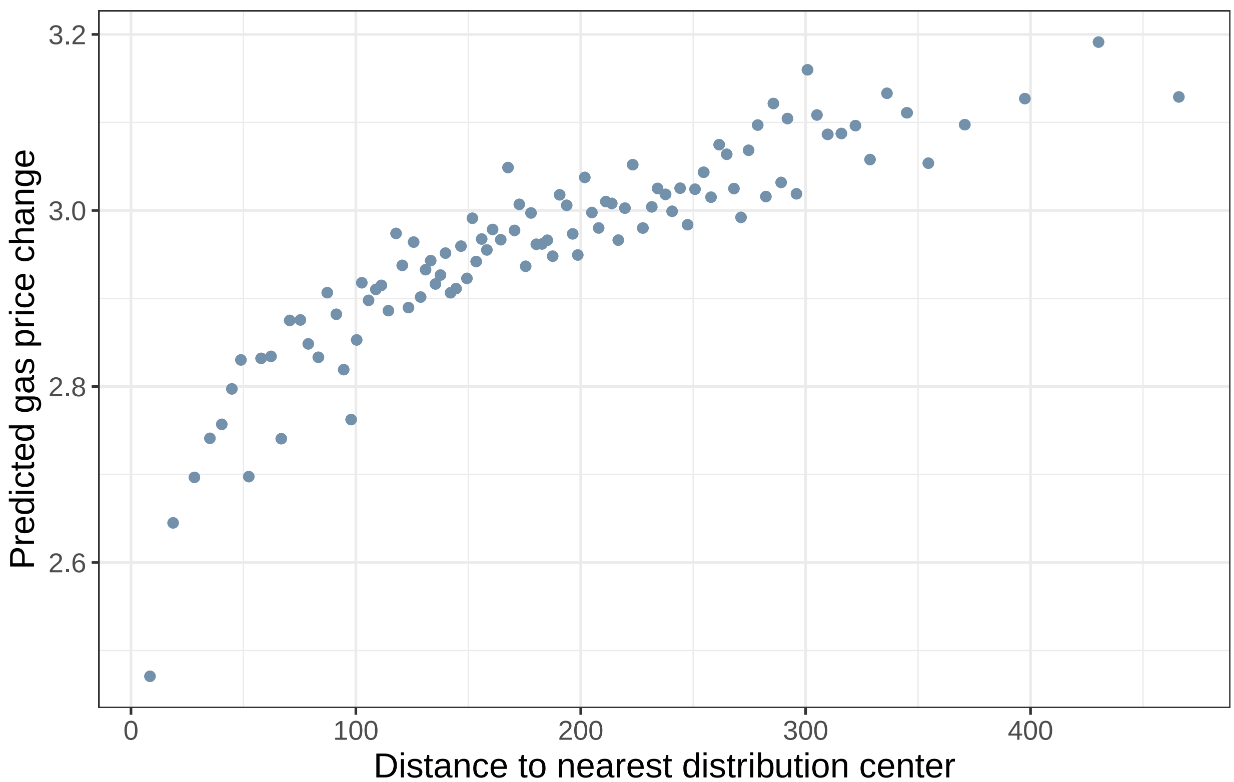
Notes: This figure shows density of stores by municipality. The different colors represent the number of stores per 100 people. While there is higher density in the central and northern parts of the country, mom-and-pop shops are prevalent everywhere in the country. To construct this map we use our novel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

Figure 7: First stage by quarter: gas prices



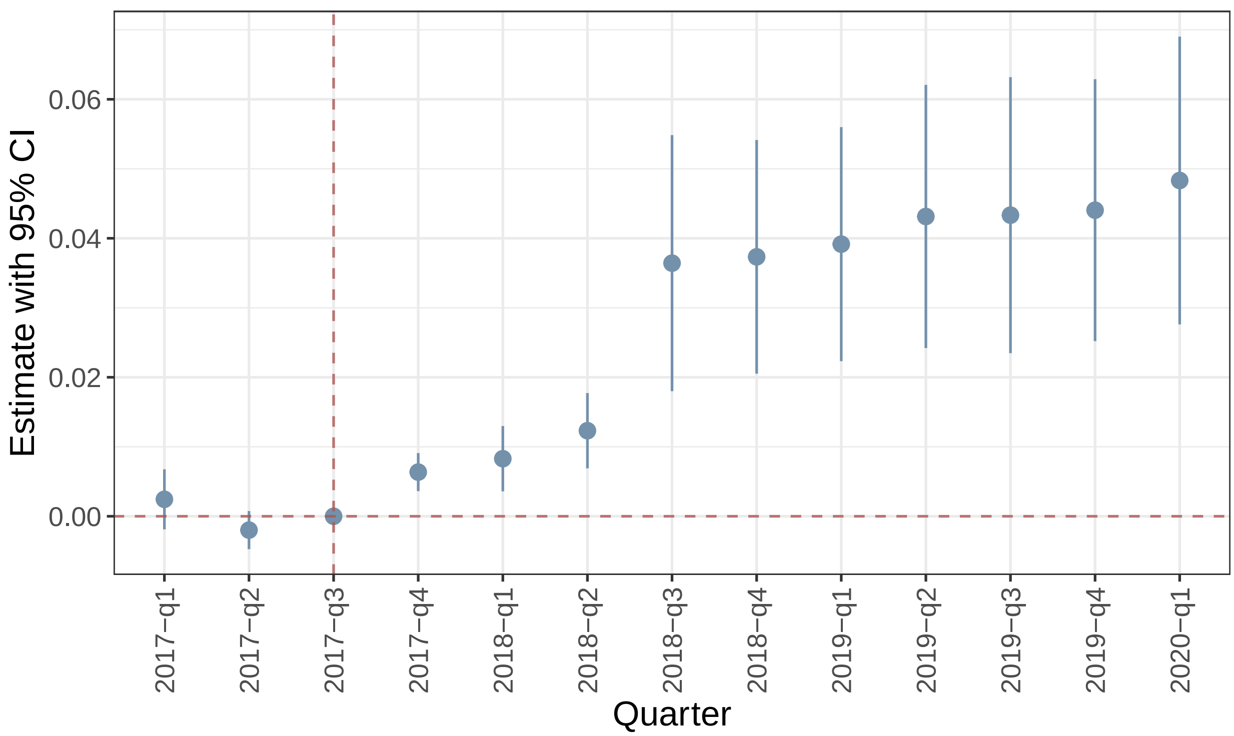
Notes: First-stage coefficients of Equation 4. Outcome is log of gasoline price. The regression includes municipality and quarter-by-year fixed effects. Baseline municipality-level controls include population, share of cars, income, and a remoteness measure that is constructed as the share of people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

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



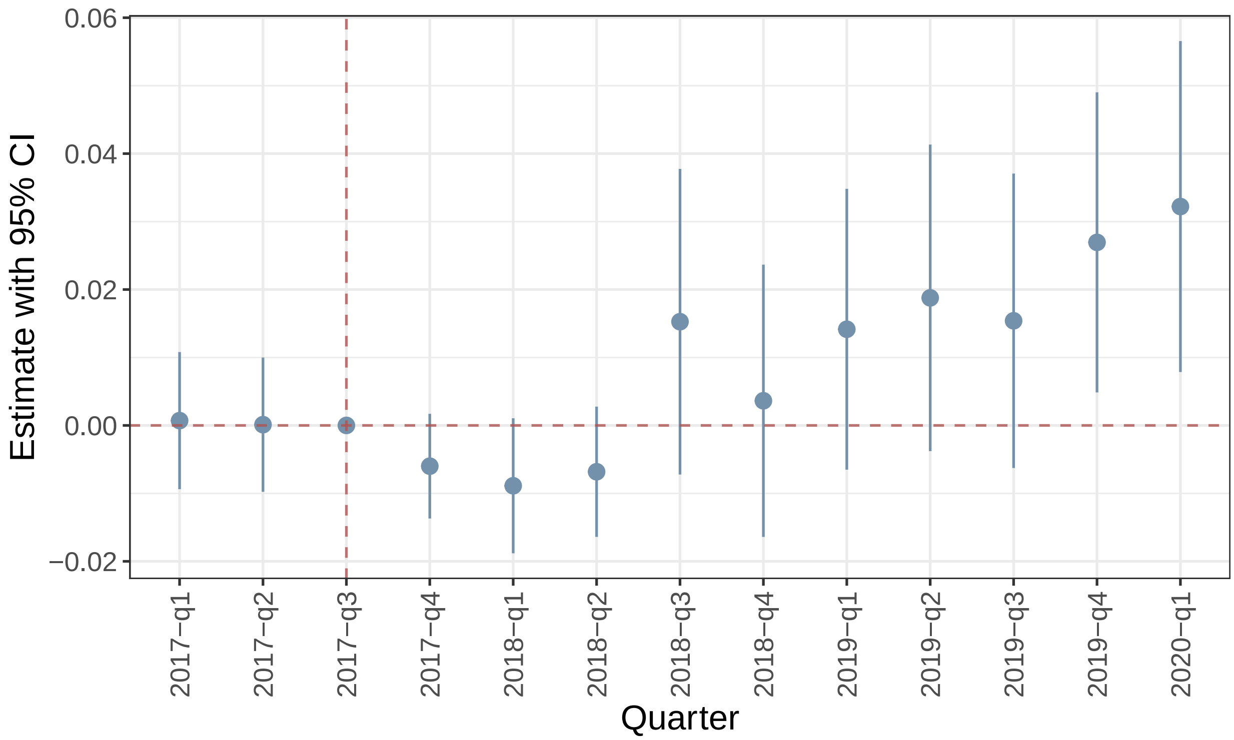
Notes: The x-axis represents the average distance from every gas station in a municipality to the closest distribution center. Each dot in the plot is the bin-mean of the predicted values from running the first-stage regression. (back to first stage discussion)

Figure 9: Reduced form by quarter: stores



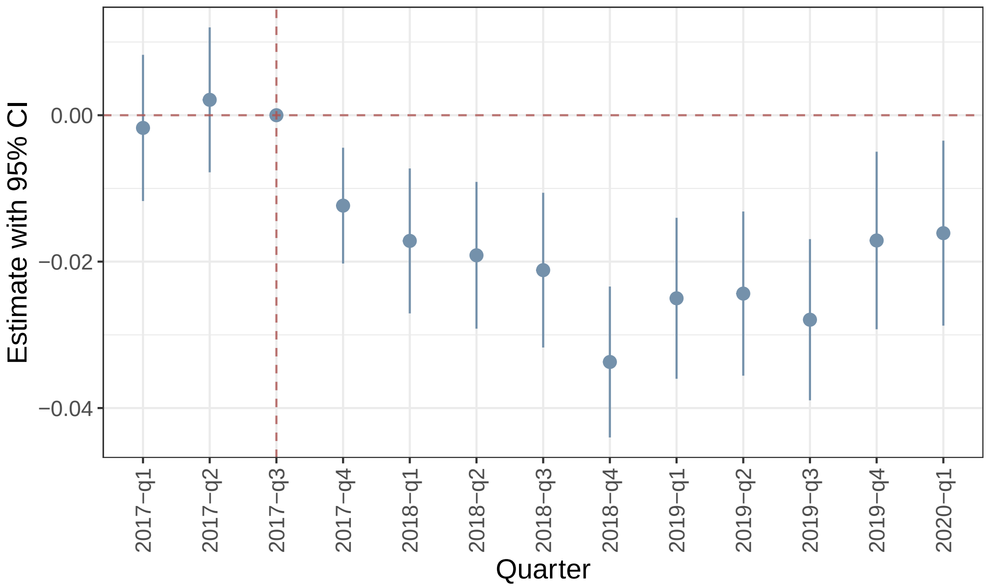
Note: Reduced-form coefficients of event study for Equation 4. Outcome is log number of stores in a quarter in a municipality. The regression includes municipality and quarter-by-year fixed effects. Baseline municipality-level controls include population, share of cars, income, and a remoteness measure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

Figure 10: Reduced form by quarter: sales

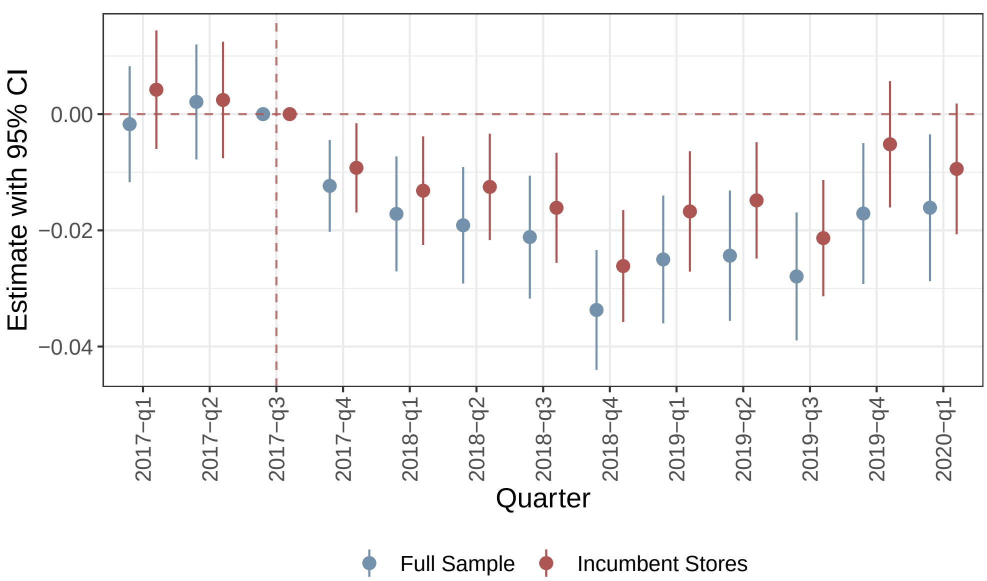


Notes: Reduced-form coefficients of event study for Equation 4. Outcome is log of aggregate sales at mom-and-pop shops in a quarter in a municipality. The regression includes municipality and quarter-by-year fixed effects. Baseline municipality-level controls include population, share of cars, income,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

Figure 11: Reduced form by quarter: average sales



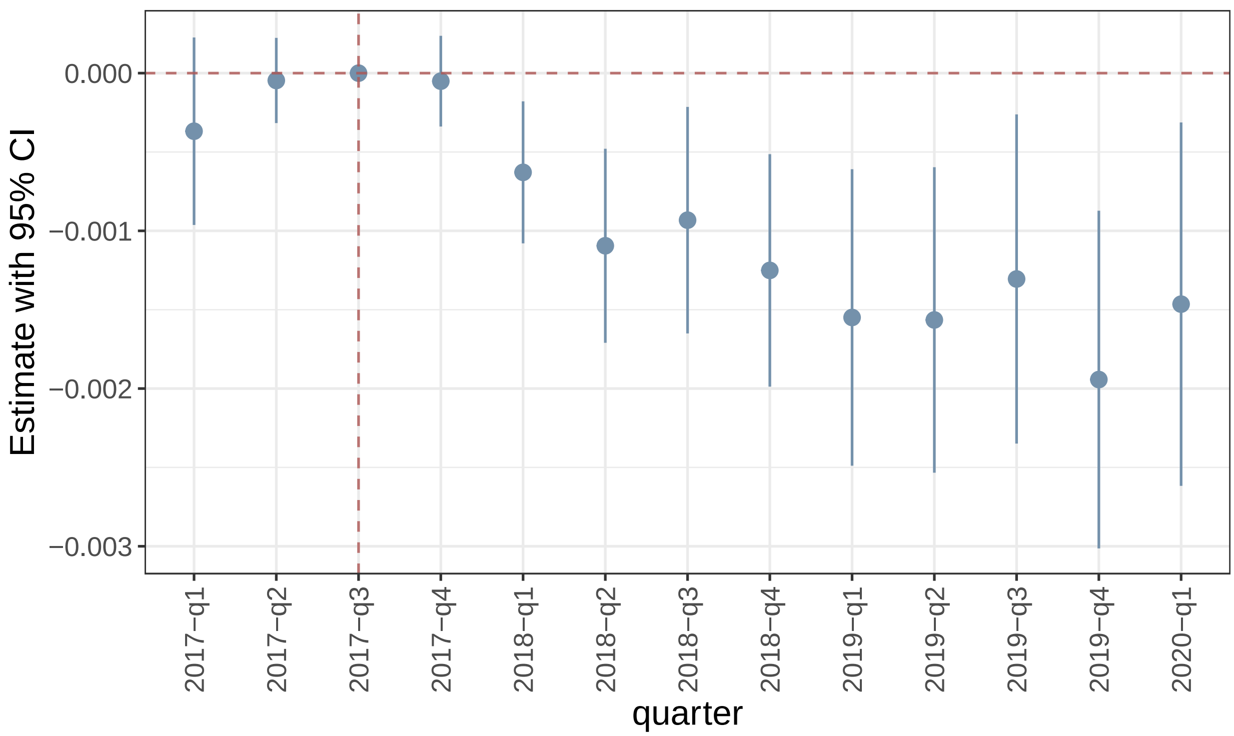
(a) Full sample



(b) Incumbent firms

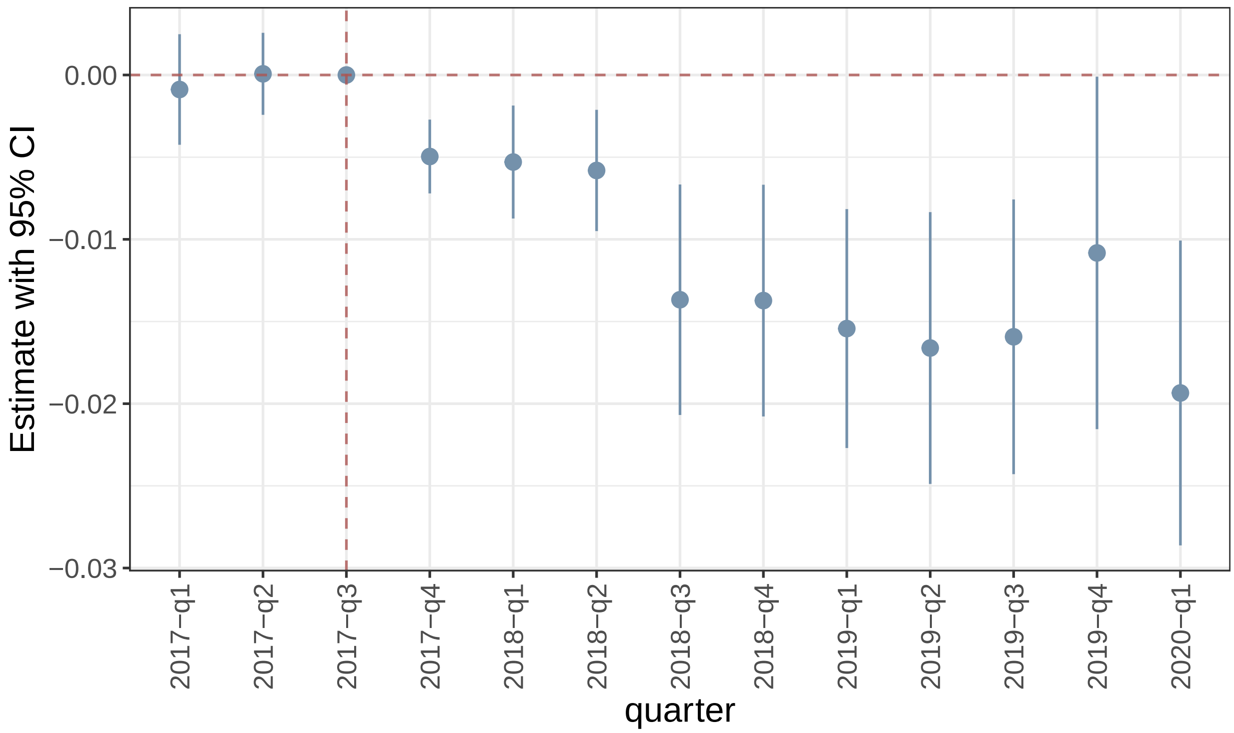
Notes: Reduced-form coefficients of event study for Equation 4. Outcome is log average sales in a quarter in a municipality. Top panel shows results using the full sample, and bottom panel adds coefficients from restricting the analysis to incumbent firms (defined as those that were operating before 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 are clustered at the municipality level. (back)

Figure 12: Reduced form by quarter: quality



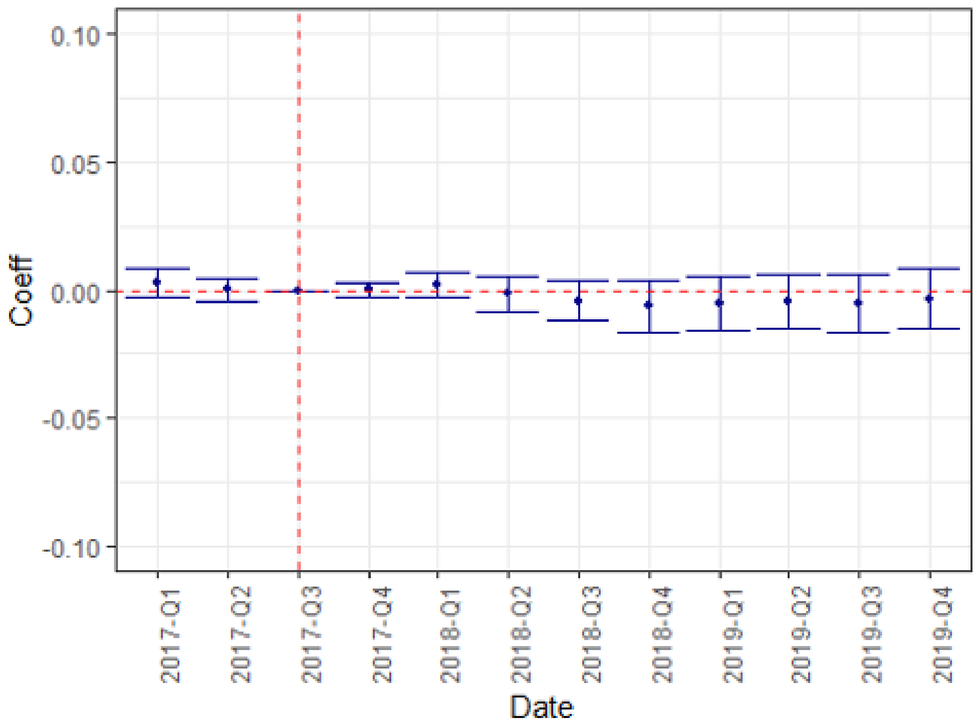
Notes: Reduced-form coefficients of event study for Equation 4. Outcome is normalized quality by municipality. Quality measure is constructed by taking firm-level fixed-effect coefficients of Equation 7. Variation is coming from change in the composition of existing firms. The regression includes municipality 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 are clustered at the municipality level. (back)

Figure 13: Average distance traveled to closest store

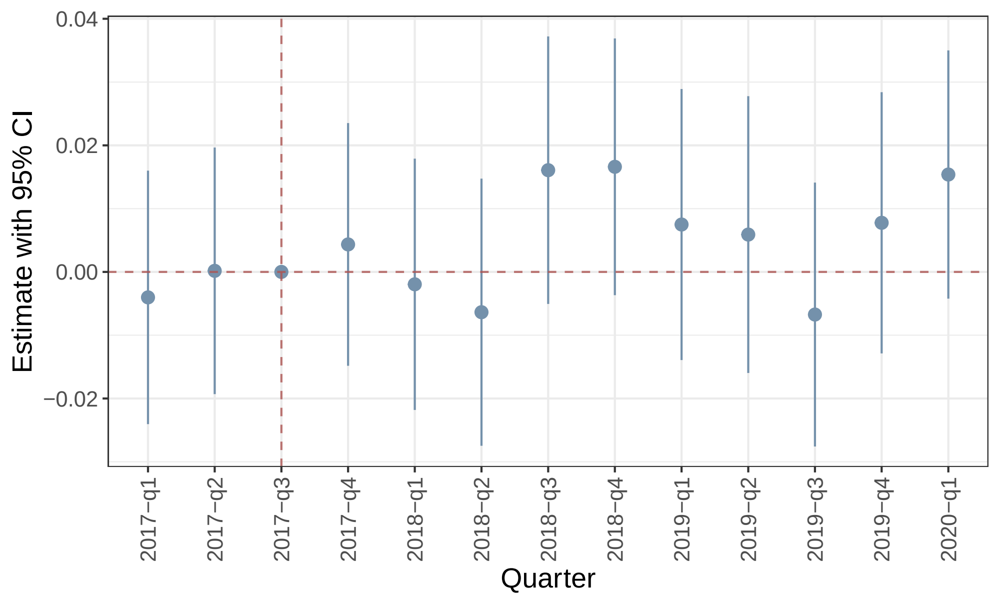


Notes: Reduced-form coefficients of event study for Equation 4. Outcome is log of average distance traveled to closest store. Distance measure is computed from a sample of 1,000 points uniformly distributed across each municipality to the closest store. The regression includes municipality and quarter-by-year 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 are clustered at the municipality level. (back)

Figure 14: Evolution of prices and wages after gas price shock



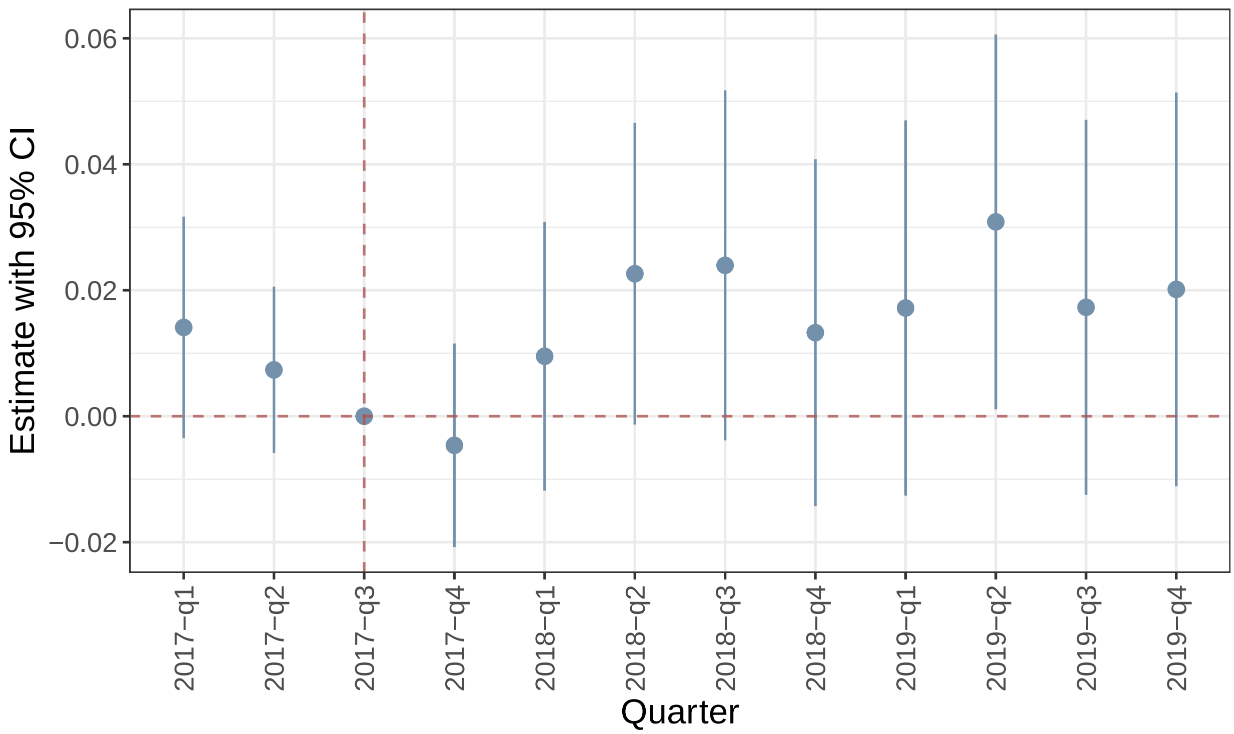
(a) Prices



(b) Nominal wages

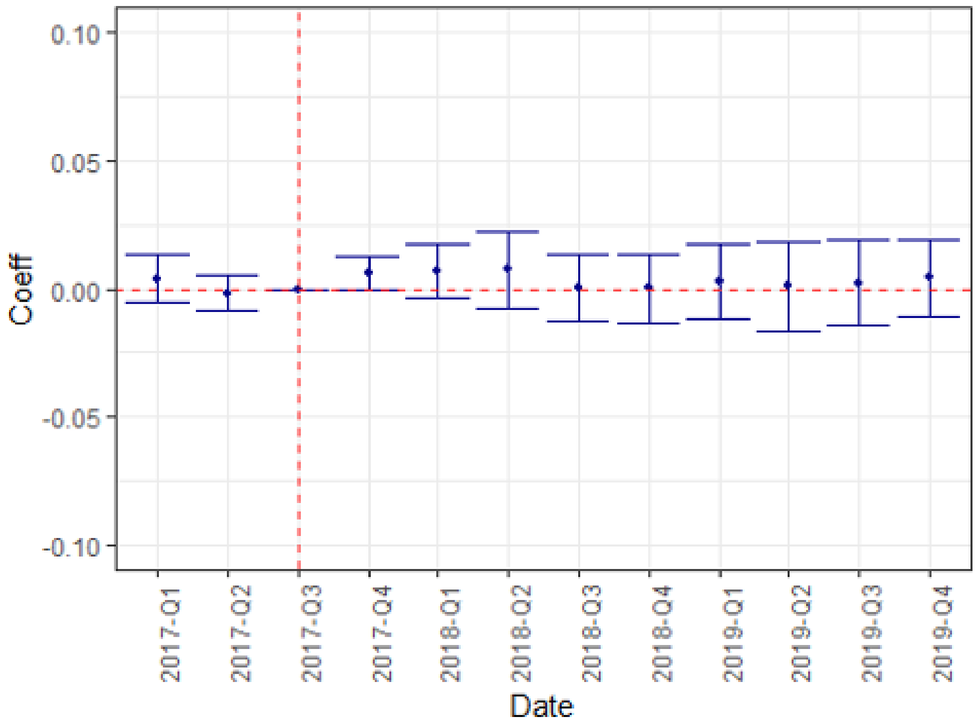
Notes: Panel A shows coefficients for Equation 9 using INEGI's barcode-level price data. Panel B shows coefficients for Equation 4 using social security data on wages. Standard errors are clustered at the municipality level. (back)

Figure 15: Evolution of employment in formal sector after gas price shock

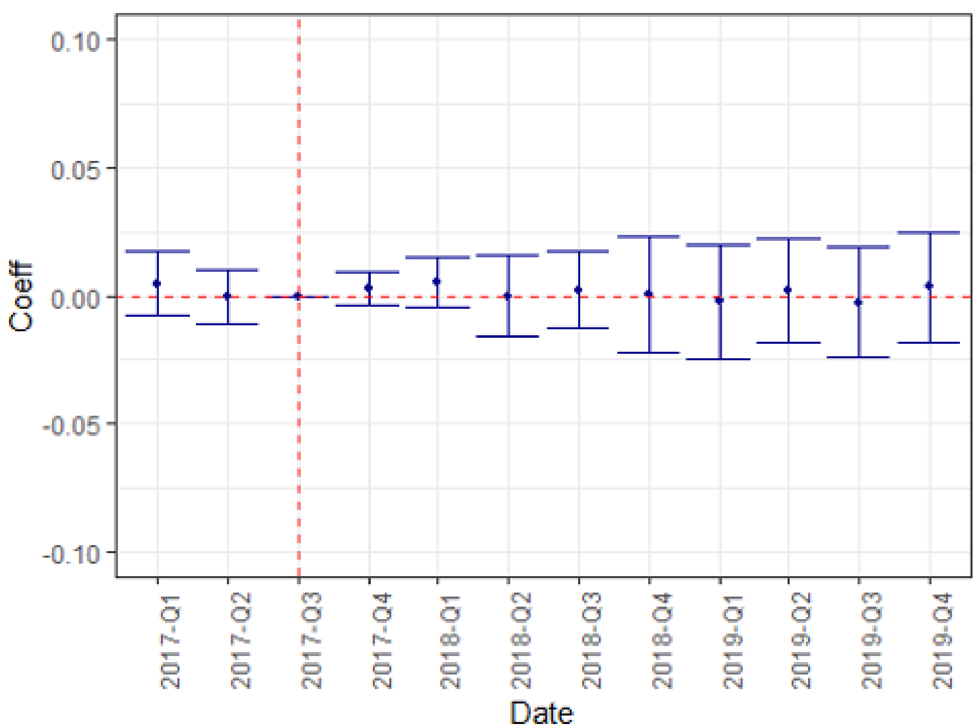


Notes: Reduced-form coefficients of event study for Equation 4. Outcome is employment in the formal sector. The regression includes municipality and quarter-by-year fixed effects. Baseline municipality-level controls include population, share of cars, income, and a remoteness measure that is constructed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

Figure 16: Evolution of prices at modern and traditional shops after gas price shock



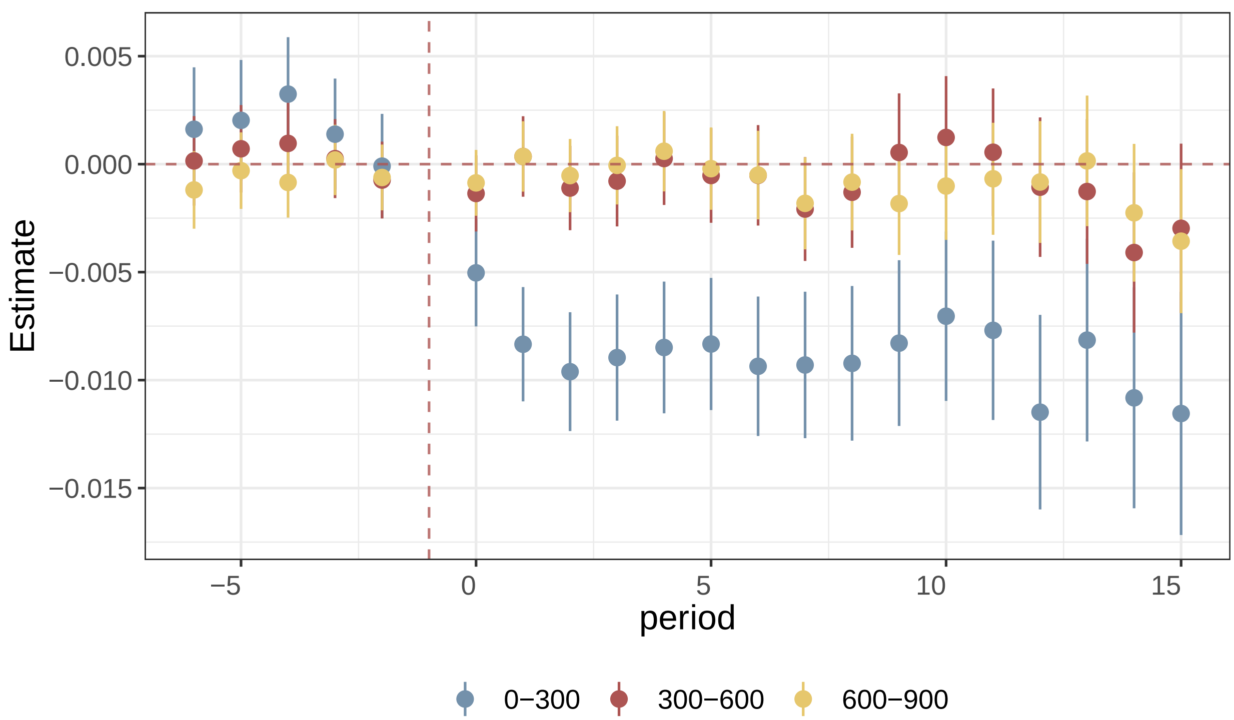
(a) Modern Stores



(b) Traditional Stores

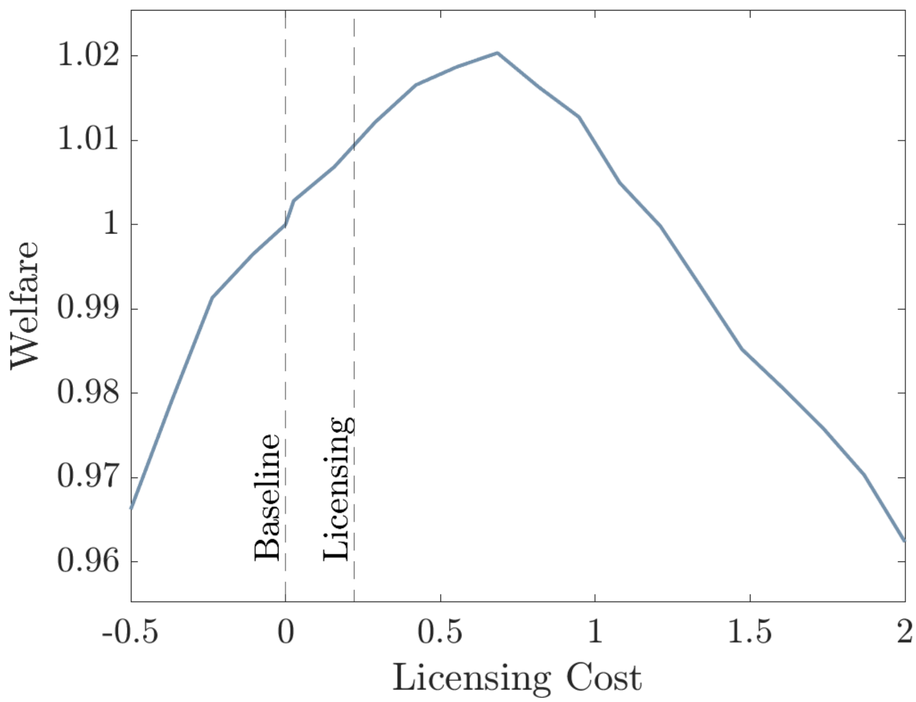
Notes: These figures show coefficients for Equation 9 using INEGI's barcode-level price data. Panel A restricts the sample to only look at prices recorded at modern stores. Panel B restricts the sample to only look at prices recorded at traditional stores. Standard errors are clustered at the municipality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

Figure 17: Spatial decay of entry on incumbents' sales



Notes: This figure shows the effect of entry on incumbents' sales. We construct rings around every entrant and estimate the effect of a new entry on incumbents' 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 18: 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 in which 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 were required by decreasing the number of stores in the market and thus increasing producer surplus (because of 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 contain information on every mom-and-pop shop our upstream supplier ever sold to from 2017 to 2020. When applicable, we converted Mexican pesos to USD at a conversion rate of MXN 18 = USD 1. (back)

Table 2: IV: Effect of gas price increases on market structure

	First Stage	IV		
Dependent Variables:	Log Gasoline Price	Log #Stores	Log Average Sales	Log Sales
	(1)	(2)	(3)	(4)
Panel A: Full Sample				
Variables				
Log Distance Distr. Center × Post	0.006***			
	(0.0006)			
Log Gasoline Price		4.88***	-3.31***	1.57
		(1.12)	(0.631)	(1.16)
Controls	Yes	Yes	Yes	Yes
Fit statistics				
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
Panel B: Municipalities without Supermarkets				
Variables				
Log Distance Distr. Center × Post	0.008***			
	(0.0010)			
Log Gasoline Price		5.85***	-4.22***	1.63
		(1.43)	(0.875)	(1.47)
Controls	Yes	Yes	Yes	Yes
Fit statistics				
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
Fixed-effects				
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 mom-and-pop shops in a municipality (Column 2), the average size of a mom-and-pop shop as measured by average sales (Column 3), and aggregate sales of mom-and-pop shops (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 variables' means are in USD (except number of stores), at a conversion rate of MXN 20 = USD 1. F-stat corresponds to Olea and Pflueger (2013) effective F-statistic. Panel A reports results for the full sample, and Panel B restricts the sample to municipalities without a supermarket. (back to first stage discussion) (back to #stores)

Table 3: IV: Effect of gas price increases on entry and exit

	Without Controls		With Controls	
Dependent Variables:	#Entry Stores	#Exit Stores	#Entry Stores	#Exit Stores
	(1)	(2)	(3)	(4)
Variables				
Log Gasoline Price	11.6***	-1.45	13.4***	-0.732
	(2.08)	(1.90)	(2.49)	(2.29)
Fixed-effects				
Quarter-Year	Yes	Yes	Yes	Yes
Municipality	Yes	Yes	Yes	Yes
Fit statistics				
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 (Columns 1 and 3) and exits (Columns 2 and 3). 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:	Log Sales			Log Stores			Log Average Sales		
Tercile:	T1	T2	T3	T1	T2	T3	T1	T2	T3
Variables									
Log Gasoline Price	0.522	2.91	-1.58**	2.32*	5.28***	2.28***	-2.06**	-1.71	-3.86***
	(1.20)	(2.04)	(0.755)	(1.21)	(1.95)	(0.831)	(0.818)	(1.07)	(0.930)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects									
Quarter-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics									
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 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	Log Average Sales
	(1)	(2)
Variables		
Log Gasoline Price	4.73***	-3.13***
	(1.05)	(0.587)
Log Gasoline Price × Q2	-0.228**	0.063
	(0.105)	(0.086)
Log Gasoline Price × Q3	-0.475***	0.191**
	(0.129)	(0.096)
Log Gasoline Price × Q4	-0.703***	0.392***
	(0.159)	(0.110)
Log Gasoline Price × Q5	-1.24***	0.672***
	(0.230)	(0.152)
Controls	Yes	Yes
Fixed-effects		
Quarter-Year	Yes	Yes
Municipality	Yes	Yes
Fit statistics		
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 types

	Extensive Margin		Frequency		Intensive Margin	
Dependent Variables:	M&P	Supermarket	Low	High	Log M&P USD	Log Super USD
	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Log Gasoline Price	0.032	-0.048	-0.381	0.059	-0.505	-0.404
	(0.116)	(0.177)	(0.326)	(0.076)	(0.537)	(0.421)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
State-Year	Yes	Yes	Yes	Yes	Yes	Yes
Municipality	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
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

Clustered (Municipality) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: IV estimates of Equation 8. Data come from INEGI's income and expenditure survey (ENIGH) from 2016, 2018, and 2020. The first two columns show extensive-margin results for which 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 the coefficients are not significant, both sets of outcomes point toward 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 margins

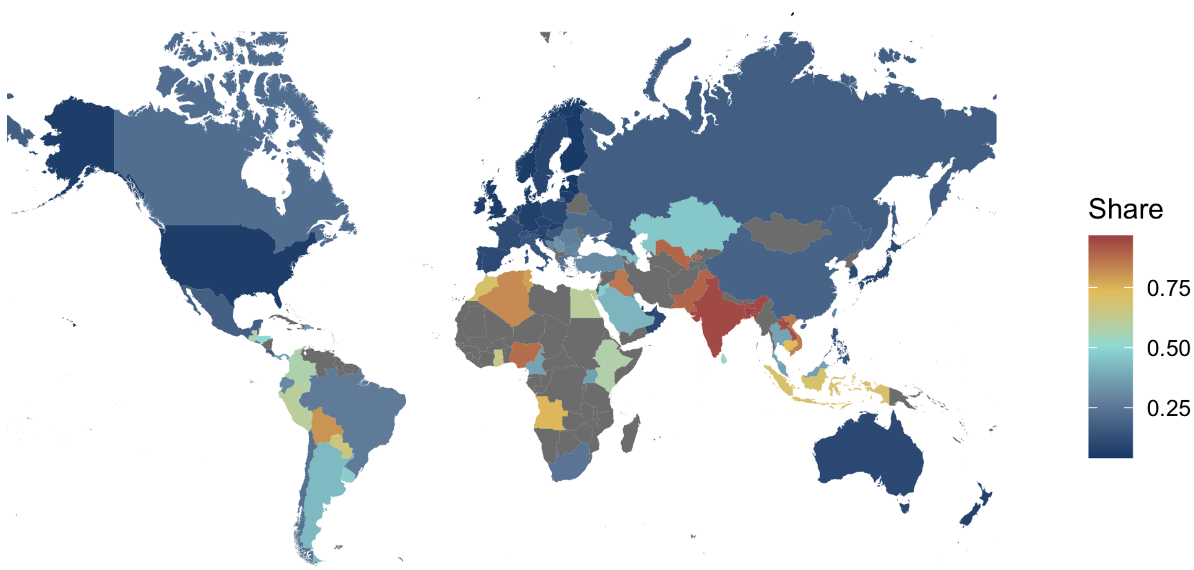
	Mobility Behavior				Within M&P Substitution
Dependent Variables:	Gasoline	Pub Trans	Log Gasoline Lts	Log Pub Trans USD	Avg Dist Traveled
	(1)	(2)	(3)	(4)	(5)
Variables					
Log Gasoline Price	-0.231	0.485***	-0.965***	0.949	-1.80**
	(0.142)	(0.183)	(0.266)	(0.998)	(0.742)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed-effects					
State-Year	Yes	Yes	Yes	Yes	Yes
Municipality	Yes	Yes	Yes	Yes	Yes
Fit statistics					
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 come from INEGI's income and expenditure survey (ENIGH) for 2016, 2018, and 2020. The first two columns show extensive-margin results for which 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 traveled 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)

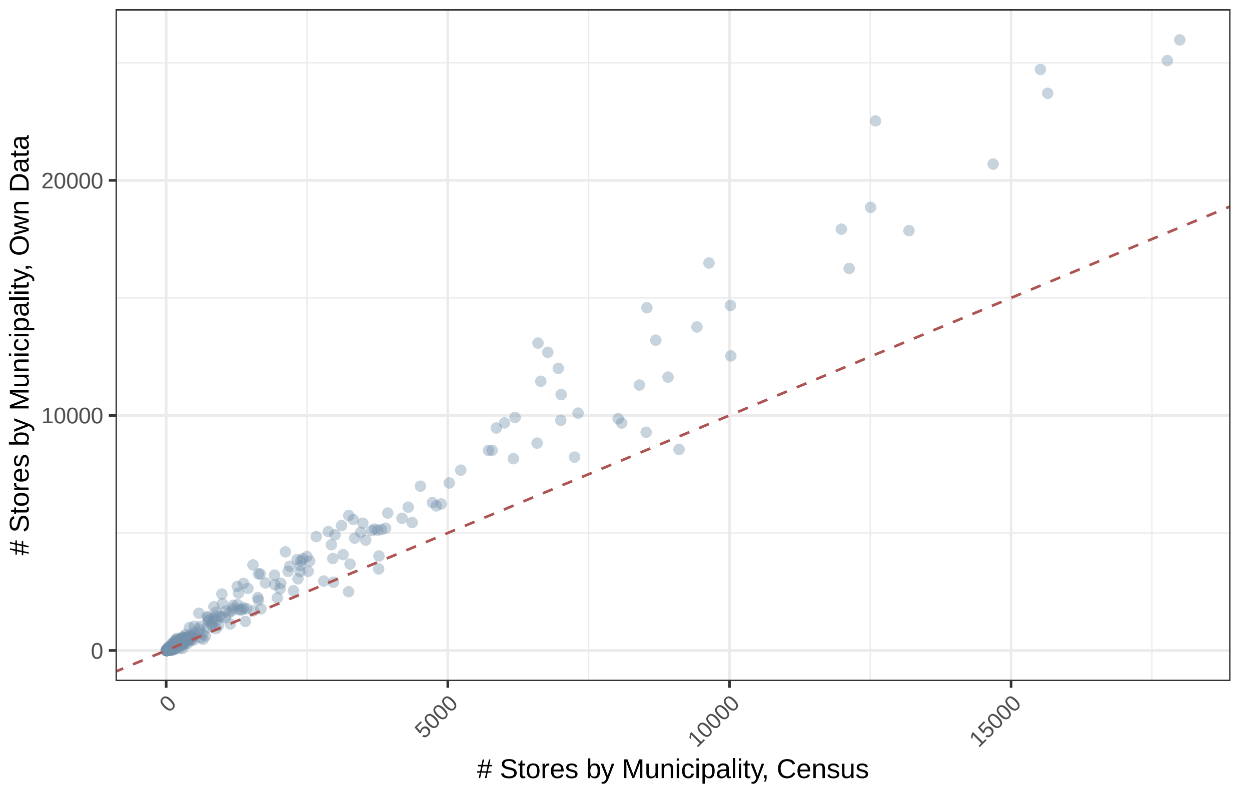
A Additional Figures

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



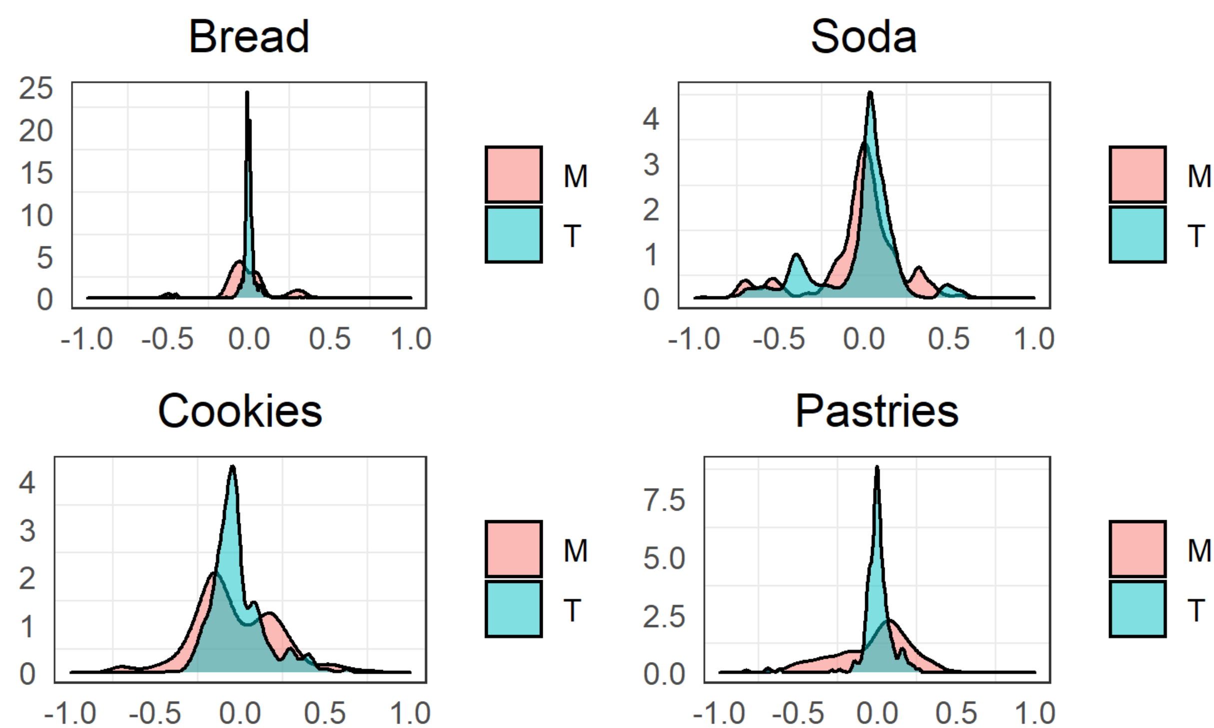
Notes: This figure shows the share of all food retail that is done in traditional stores. Data used to construct this map comes from Euromonitor's 2019 report. Countries in gray indicate that no data was available. (back)

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



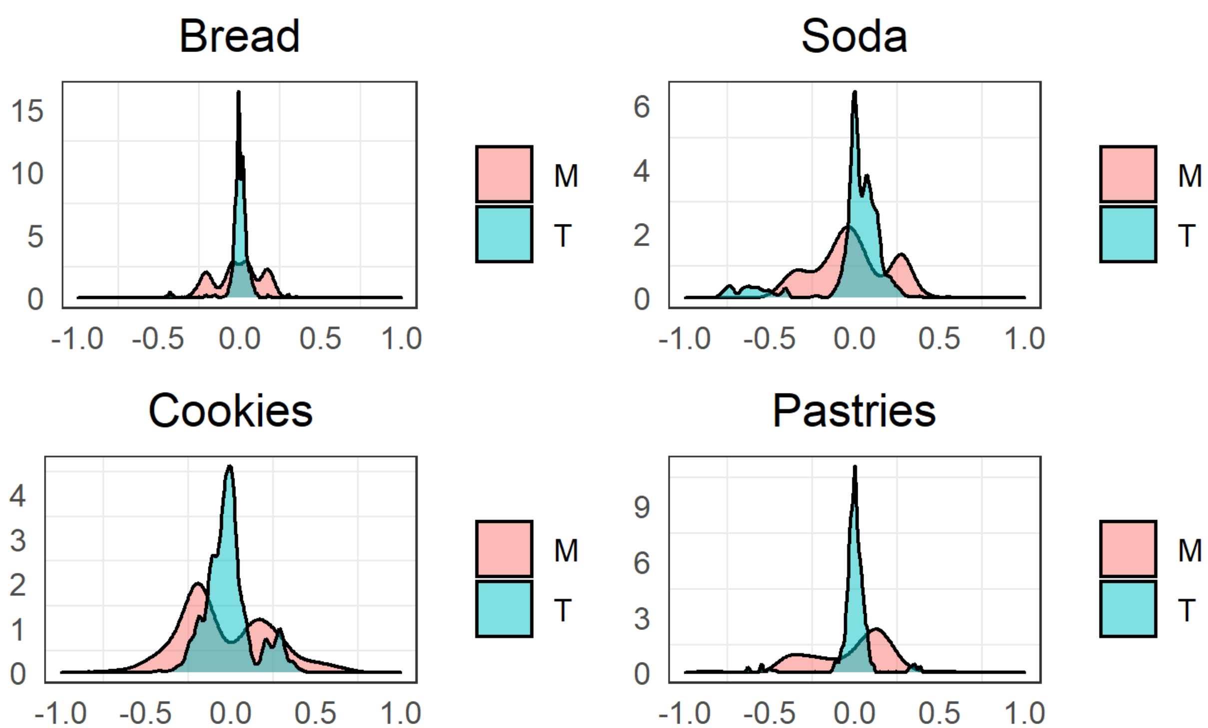
Notes: We plot the number of mom-and-pop shops contained in our data in 2019 for every municipality (y-axis) against the number of shops that appear in INEGI's 2019 DENUE. THe DENUE is the official registry of firms which comes from the Economic Census of 2015 and is updated yearly. Each dot represents 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



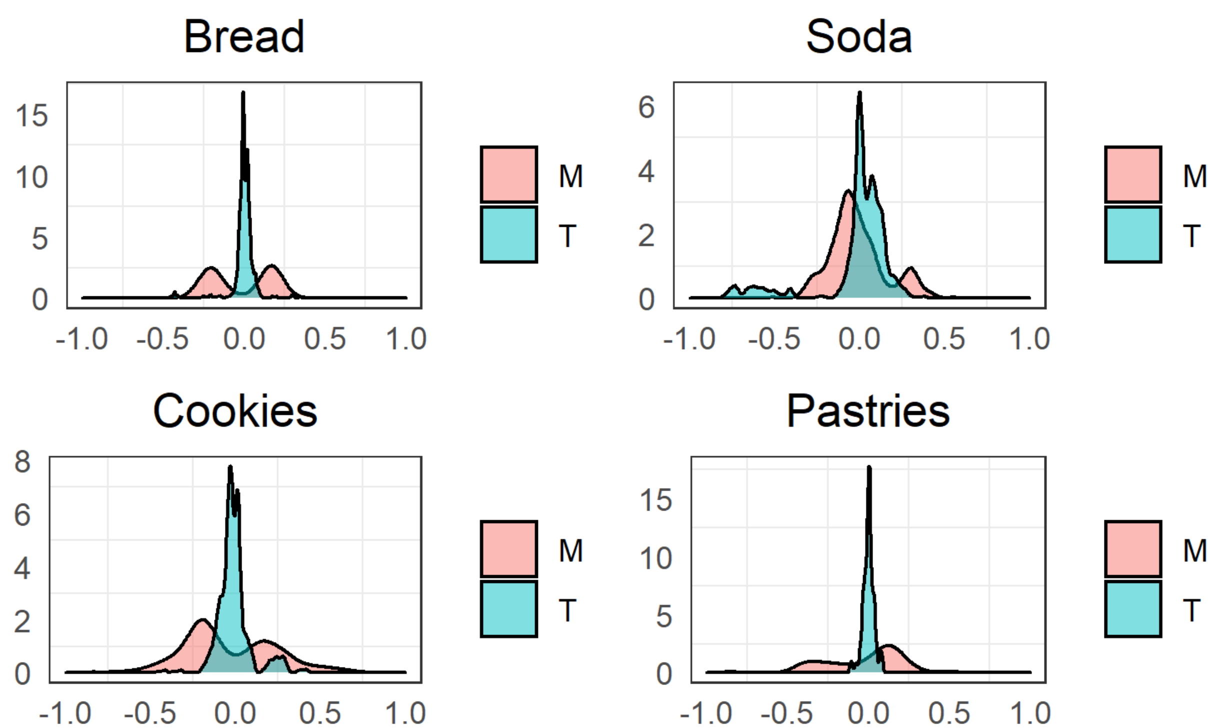
Notes: Figure displays kernel estimates of the log price distribution pooled over store format and months. Log prices refer to final consumer prices and are expressed as deviations from the month's average. All the variation observed is within month. T refers to traditional shops and M refers to modern 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.



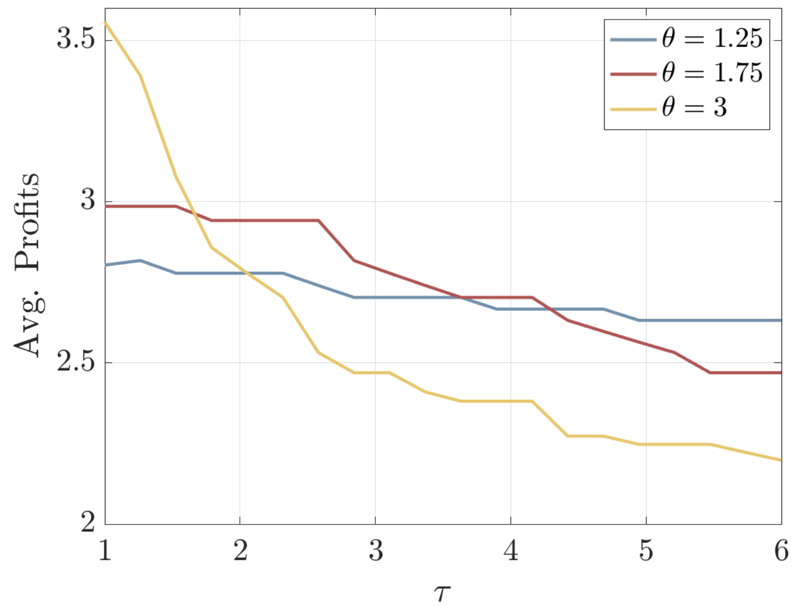
Notes: Figure displays kernel estimates of the log price distribution pooled over store format and months. Log prices refer to final consumer prices and are expressed as deviations from the month-state average. All the variation observed is within month-state. T refers to traditional shops and M refers 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.

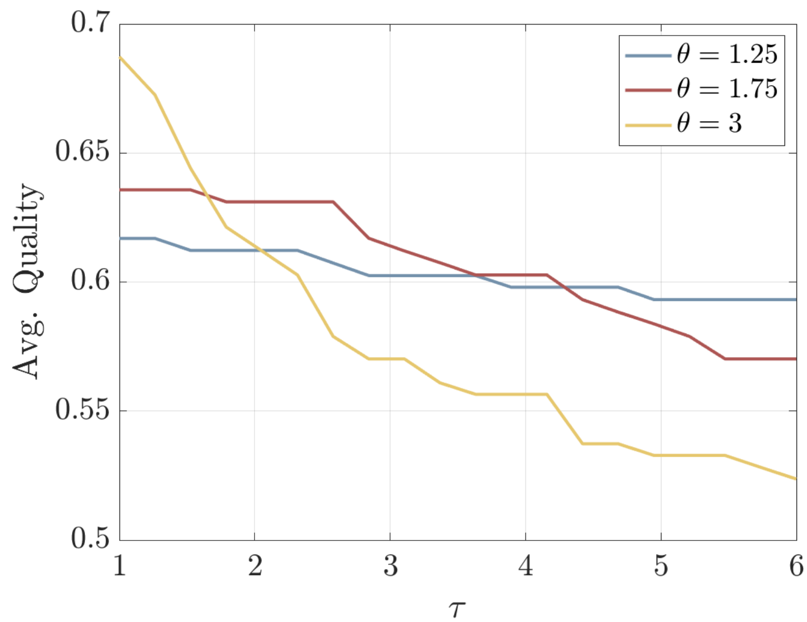


Notes: Figure displays kernel estimates of the log price distribution pooled over store format and months. Log prices refer to final consumer prices and are expressed as deviations from the month-municipality average. All the variation observed is within month-municipality. T refers to traditional shops 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



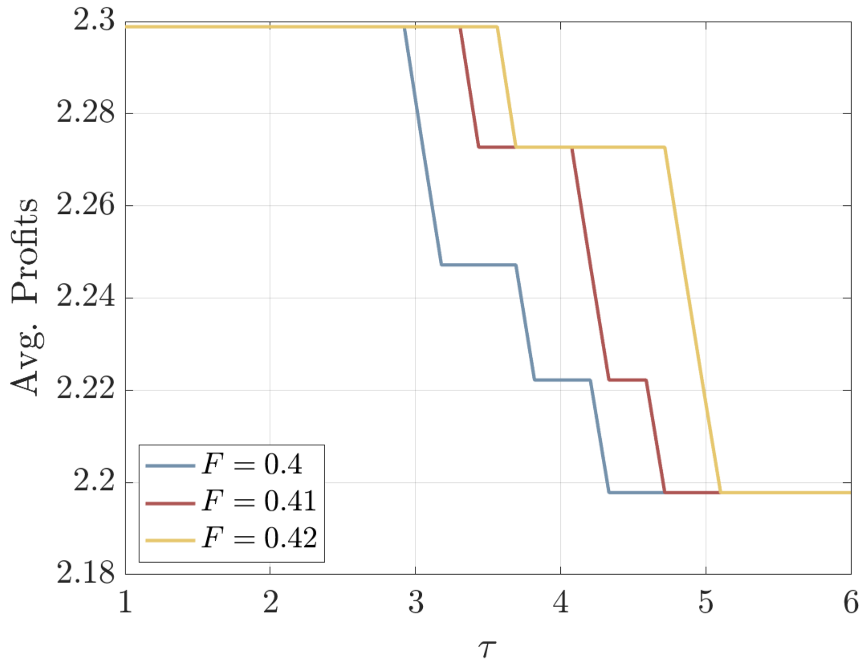
(a) Effect on profits



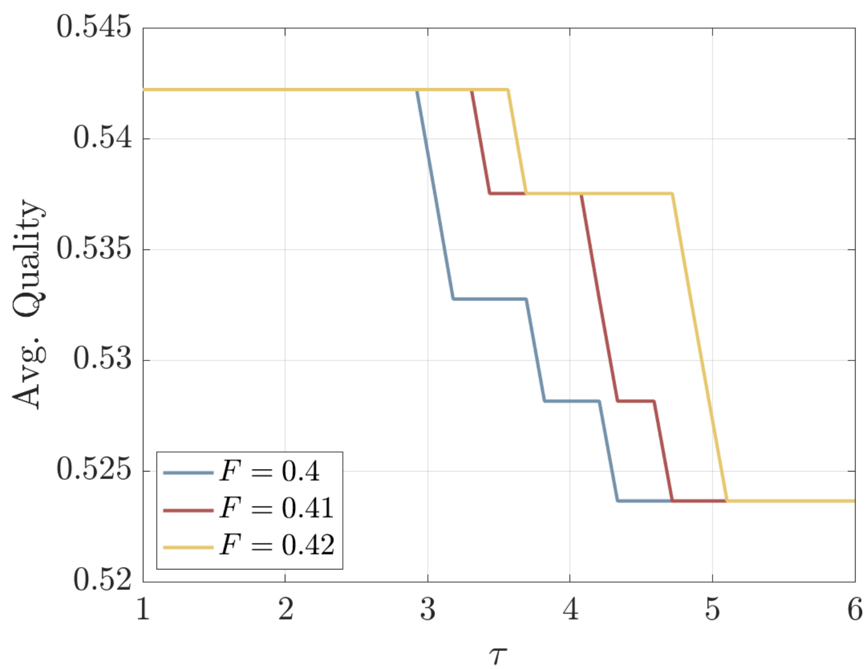
(b) Effect on quality

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



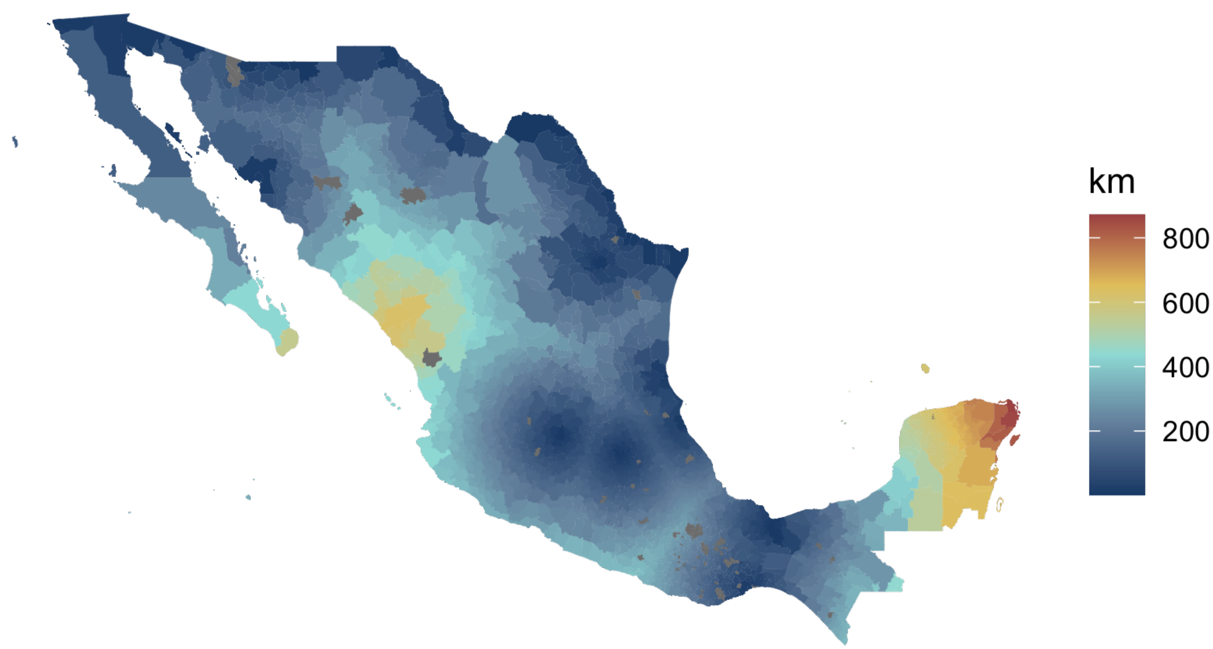
(a) Effect on profits



(b) Effect on quality

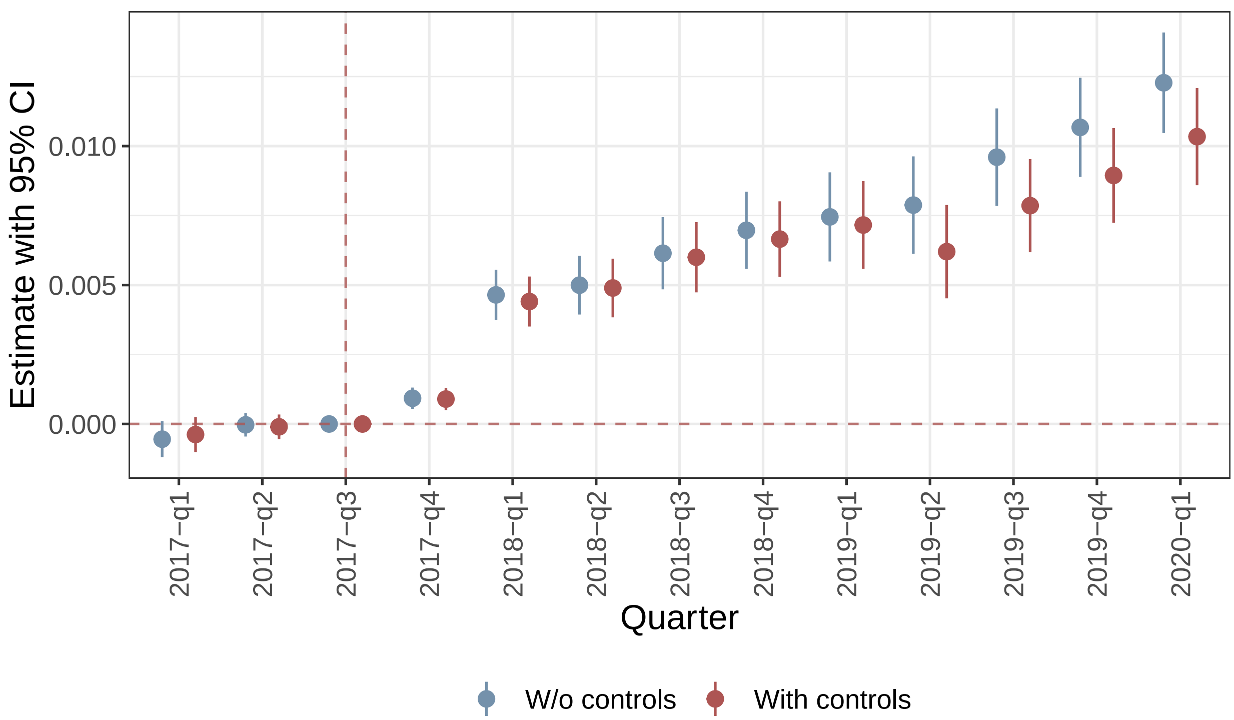
Notes: These figures are simulations using the model to show how increases in transport costs affect average profits (Panel A) and average quality (Panel B) for different value of F. When F is low, increases in transport costs lead to a larger drop in profits and quality. (back)

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



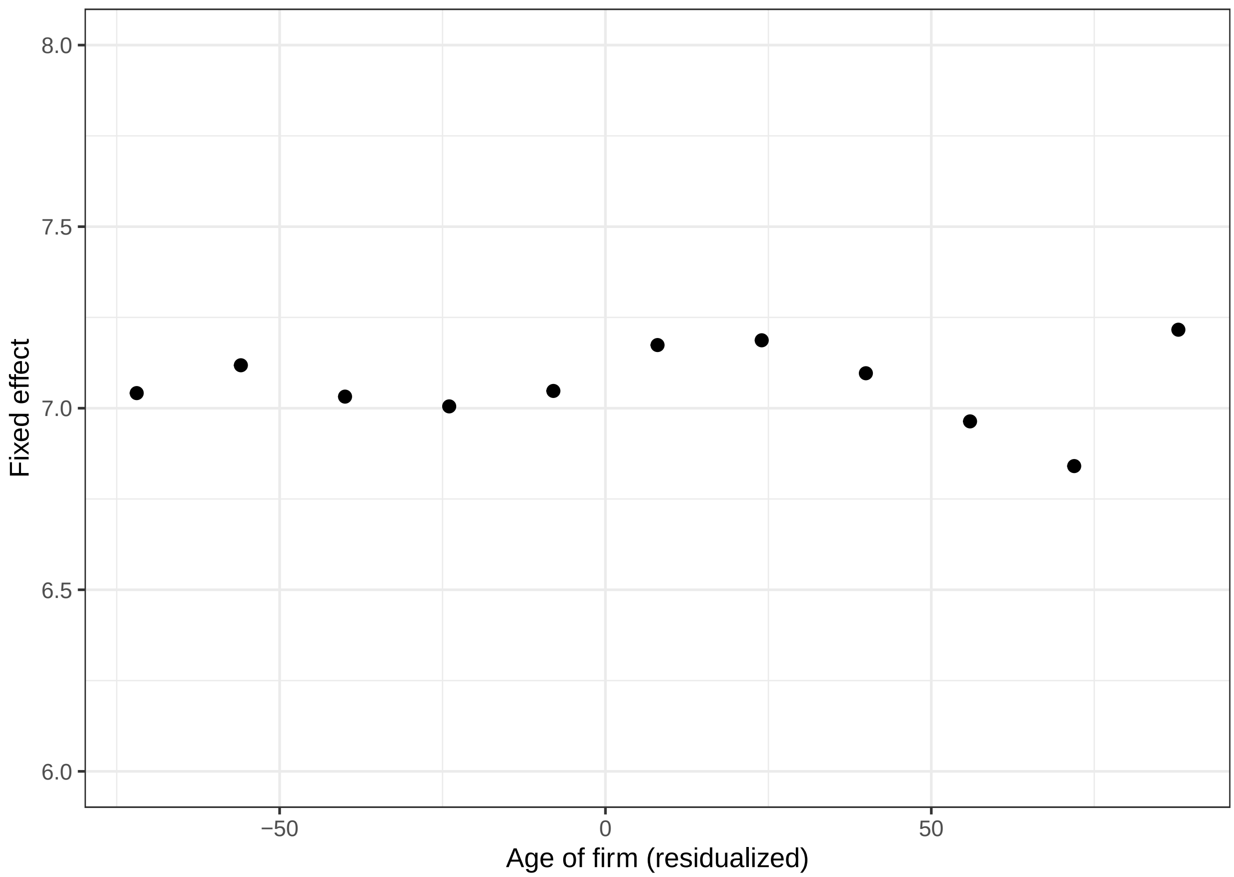
Notes: Map shows the distance in kilometers from each municipality to the closest distribution center. In order to calculate the distance, we use the coordinates of every gas station in a municipality and compute the distance to the nearest distribution center. We average over all distances within a 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



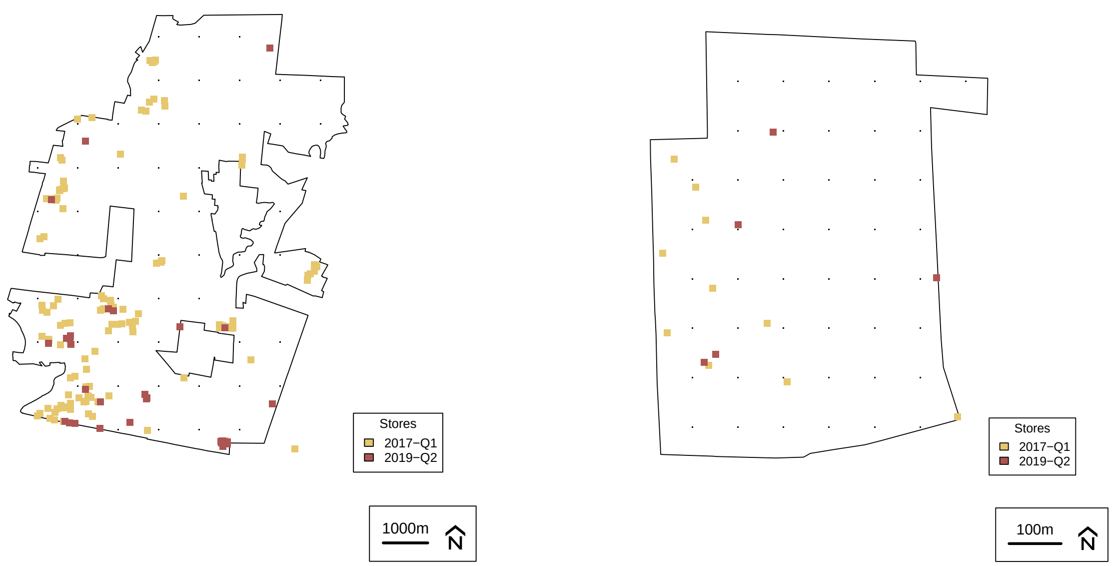
Notes: First stage coefficients of Equation 4 with and without controls. Outcome is log of gasoline price. The regression includes municipality and quarter-by-year fixed effects. Baseline municipality level controls include population, share of cars, income and a remoteness measure that is constructed 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)

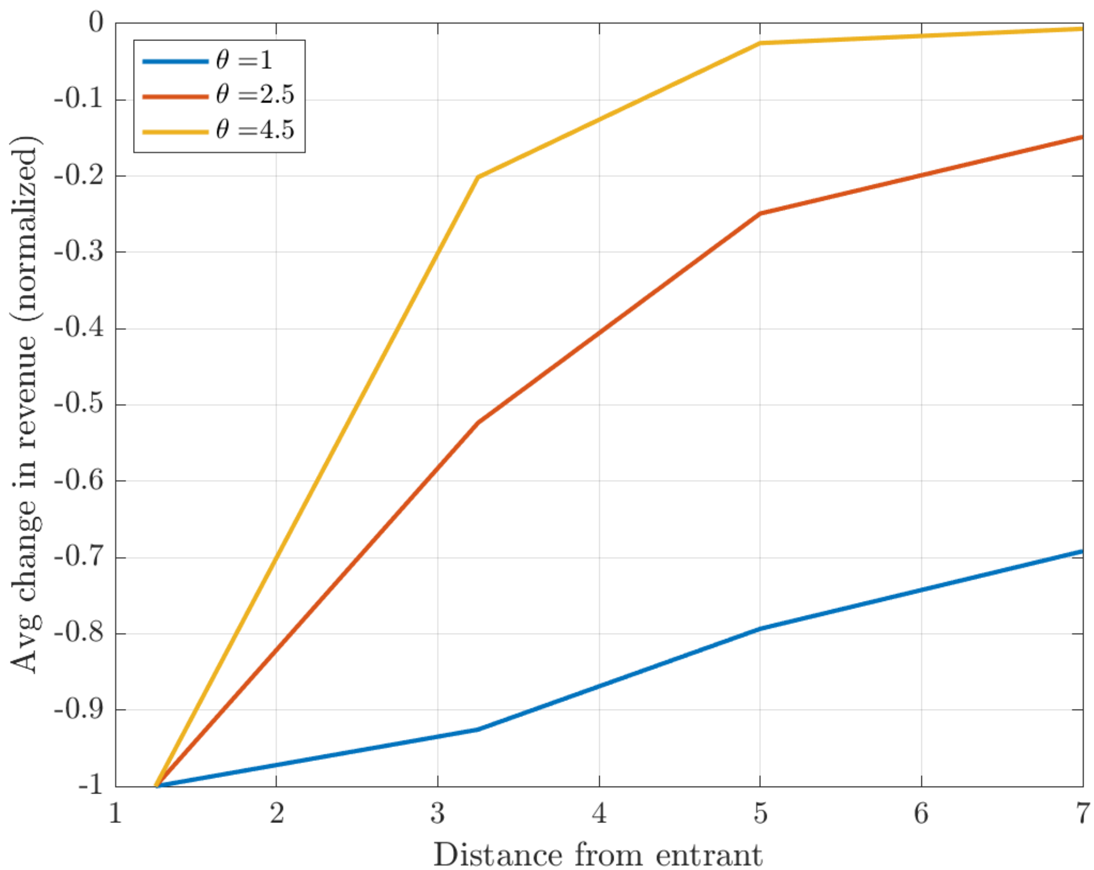
Figure A.11: Example of store entry effect on consumer market access



(a) (b)

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 (that is, 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 farther 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 Fixed cost of entry reduced-form

As an additional exercise we ask whether stores that enter in places where gas prices increased more have lower fixed cost of entry. We do not have information on how much stores pay in fixed cost but we can use two different measures that serve as proxies. The first one is an index constructed by the National Council for the Evaluation of Social Development Policy (CONEVAL) and the second uses real estate values in Mexico City.

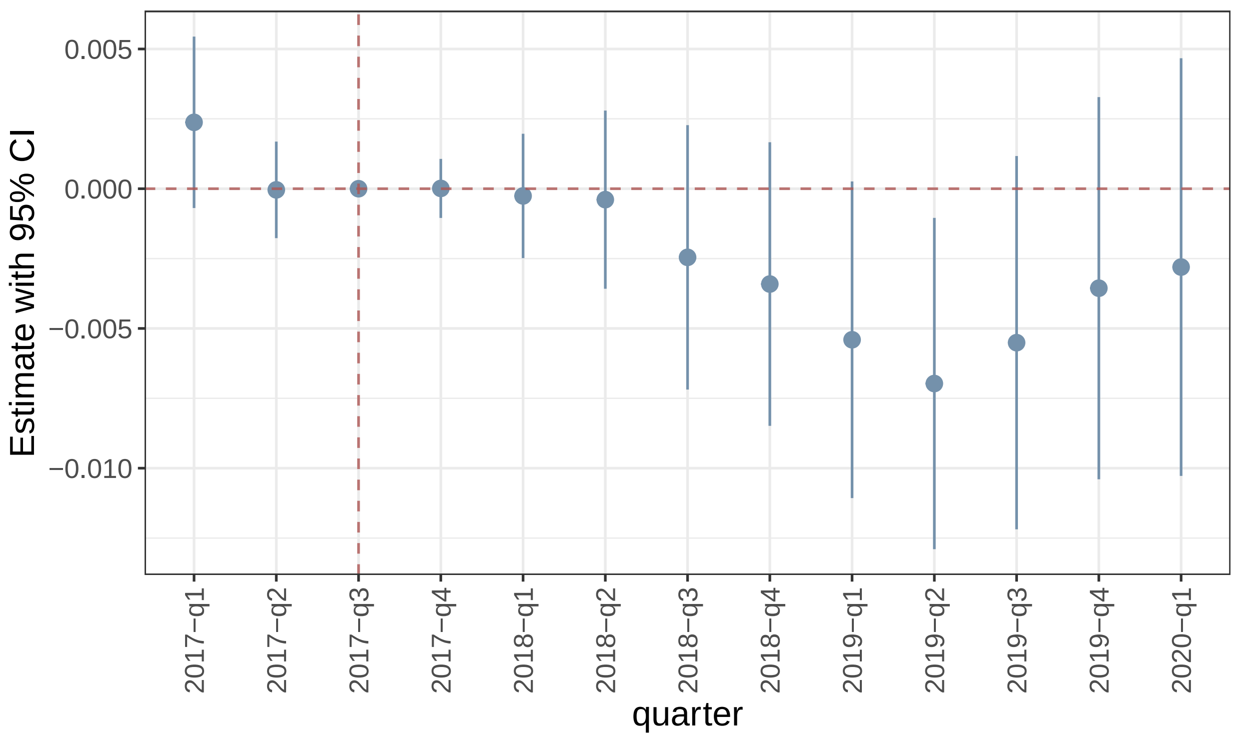
The index used as our first proxy is calculated via a principal component analysis and captures the level of development of each locality.[27] We think this measure captures relevant information about households like size, which would be informative of how much they pay to set up their shops (given that many shops open in an owners residence). The advantage of this measure is that we can observe it at the locality level for the whole country. We assign the pre-deregulation index value to every store in our data set (two stores in the same locality have the same fixed cost of entry proxy). We then construct a municipality by quarter level measure of fixed costs of entry taking the average over all stores operating in that quarter. Similar to our quality measure, all the variation is coming from the fact that different stores are operating in every period.

Figure B.1 plots the coefficients from running our standard event study specification (Equation 4) with average fixed cost of entry as our outcome variable. We can see that starting in the third quarter of 2018, fixed costs of entry fall suggesting that entrants in municipalities farther away from gasoline distribution centers pay less in fixed costs than entrants in municipalities that are closer. The drop coincides with the larger increase in number of stores.

A second, perhaps better measure we can use to proxy fixed cost of entry are real estate values which are correlated with rental prices. While we have established that most store-owners open their shops in their own residential space, we think of rental prices as the opportunity cost of what they could be doing with that space. The disadvantage with this measure is that it is only available for Mexico City and thus our results are very noisy. We construct our outcome variable in the same way as before, we assign every store a fixed cost of entry based on the pre-deregulation real estate value of their locality and aggregate everything at the municipality-quarter level. Results are shown in Figure B.2. Using this measure we also find a decrease in average fixed cost of entry being paid in municipalities farther away from distribution centers.

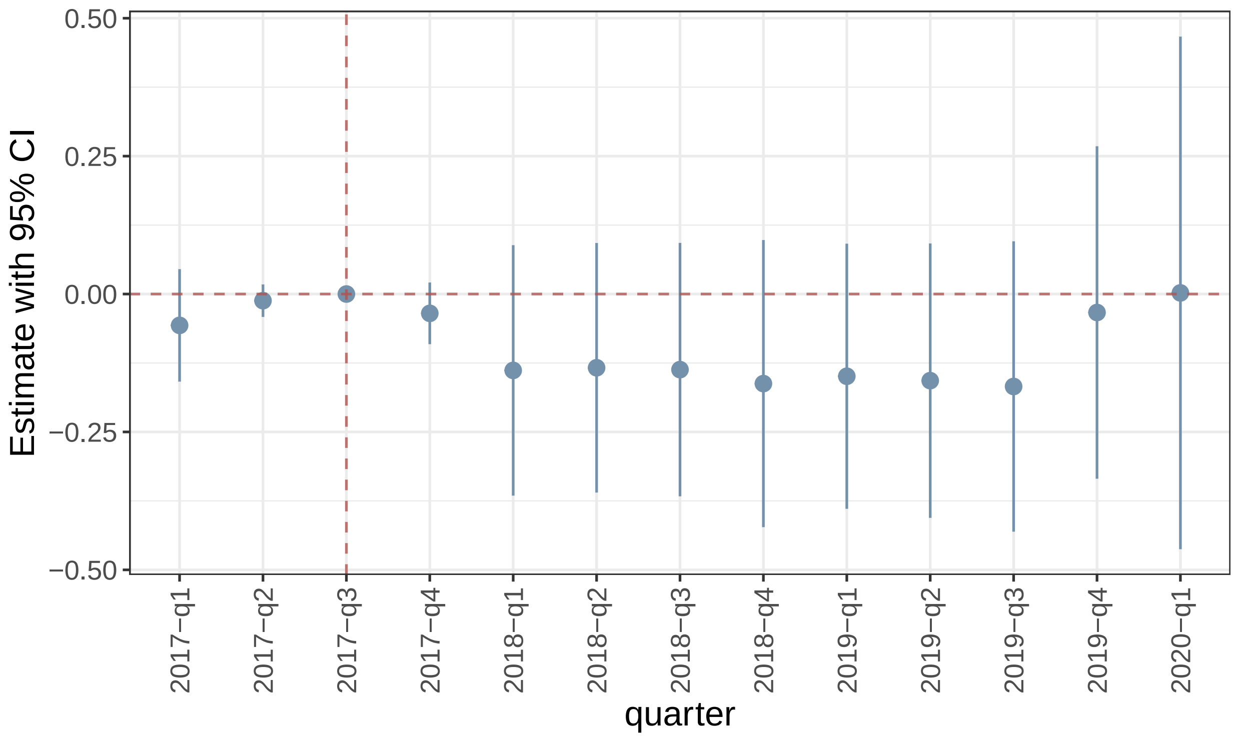
[27]The index summarizes variables regarding education, access to health services, quality and size of households, access to basic services in the house (bathroom, running water, electricity, etc.) and ownership of capital goods (fridge and washing machine) at the census tract level. All variables come from the 2010 demographic census.

Figure B.1: Reduced form by quarter: fixed cost of entry (CONEVAL index)



Notes: Reduced-form coefficients of event study for Equation 4. Outcome is normalized fixed cost of entry as measured by our CONEVAL 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 are clustered at the municipality level.

Figure B.2: Reduced form by quarter: fixed cost of entry (CONEVAL index)



Notes: Reduced-form coefficients of event study for Equation 4. Outcome is average fixed cost of entry as measured by real estate prices. 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 are clustered at the municipality level.

C Theoretical Derivations

C.1 Business Stealing

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

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

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:

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

C.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:

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

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:

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

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

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

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:

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

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

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

Plugging in results from above, we get:

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

Which can be further decomposed into:

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