Building Up Local Productivity:
Infrastructure and Firm Dynamics in Mexico

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Abstract

What determines the aggregate and distributional effects of new transportation infrastructure? One key overlooked channel is the role that infrastructure policy plays in changing the incentives of firms to enter, exit, and grow – in turn generating endogenous changes in local productivity. In this paper, we document and quantify the importance of this channel by using detailed Mexican microdata and a spatial general-equilibrium model that incorporates firm dynamics. Leveraging random delays in the construction of highways, we empirically show that productivity grows in places with better transportation infrastructure. Firms play a critical role in driving this results: highways increase firms' size, entry rates, survival rates, and total factor productivity. Calibrating our model on census data between 1998 and 2018, we find that new highways over this period increased welfare and income by half a percent, similar to its costs in terms of GDP. Moreover, we find substantial spatial reallocation of workers and production. Nearly half of these effects are explained by endogenous changes in local labor productivity, which is driven by firm dynamics.

Keywords: Economic geography, firm dynamics, infrastructure

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1 Introduction

Transportation infrastructure is a key determinant of economic development because it reduces trade costs and travel times for moving both goods and people, bolstering GDP and welfare (Banerjee et al., 2020; Allen and Arkolakis, 2022). Over the past years, economic geography models –the workhorse spatial framework to study transportation infrastructure– have emphasized the importance of locations' characteristics to understand the aggregate and distributional effects of such policies (Allen and Arkolakis, 2014; Redding and Turner, 2015). In this literature, locations are characterized by two fundamental features: 1) amenities, which include housing, weather, cultural attractions, and personal connections; and 2) local productivity, explaining why the same worker may be more productive in one place than in another. While the literature has shed light on key components of local amenities, such as housing supply or public goods congestion, it remains a challenge to understand what determines local productivity, which is often viewed as an exogenous feature mostly subject to agglomeration forces.

In this paper, we argue that local productivity is shaped by firm dynamics – that is, the endogenous processes of entry, exit, and growth; and, moreover, that such firm dynamics are a key driver of the effects of new transportation infrastructure. We support this idea by answering the following two research questions: Does new transportation infrastructure affect firm dynamics and local productivity? And, to what extent do firm dynamics drive the aggregate and distributional effects of infrastructure policy? We tackle the first question empirically by using firm-level panel data from Mexico and leveraging a natural experiment arising from highway planning and execution nationwide over two decades. We answer the second question quantitatively by proposing an economic-geography model à la Allen and Arkolakis (2014), extended with firm dynamics in the spirit of Melitz (2003).

Our central empirical result is that improvements in transportation infrastructure do, in fact, lead to local productivity growth, and that this increase is connected to changes in firm dynamics. These findings are based on two main data sources. First, the Mexican Economic Census, a detailed panel data set covering the universe of firms across all locations in the country. Second, the National Highways Network, a comprehensive digitization of all paved roads in Mexico – allowing us to fully characterize the dynamics of firms and the evolution of transportation infrastructure over a 20-year period, from 1998 to 2018.

The main empirical challenge is reverse causality, a concern because it is plausible that economic outcomes determine where the government chooses to build new highways. To overcome this issue, we implement a *delayed planned construction* approach by digitizing the placement and characteristics of 250 highways that were planned over the period from 2007 to 2018. In Mexico, presidents present their national highway construction plans when they begin their term, and they provide Congress with detailed progress reports throughout their tenure. We use these reports to track the execution status of the plans and their exact construction timing. The identifying assumption is that, while placement of construction plans may be influenced by demographic, political, and economic factors, the timing of actual execution, conditional on its previous selection, is as good as random.

Leveraging this source of variation, we estimate a staggered differences-in-differences model following Callaway and Sant'Anna (2021) for two sets of construction plans between 2007 and 2018. We categorize a firm as *treated* if it operates in a location close to an executed construction plan and as *not yet treated* if it is close to a plan that was not executed. We exclude from the sample all firms far from construction plans. Although this treatment is binary, we show that it implies significant increases in market access for treated locations.

According to our baseline point estimates, during the treatment period, workers in treated locations increase their labor productivity by around 5%. This can be explained by two mechanisms. First, firms in treated locations are themselves 2% more productive. Second, these firms also become 2% larger. Thus, local labor productivity grows because more workers are employed by more productive firms. Firms also become more likely to survive, generating persistence in the productivity composition of firms in treated locations. After five years, both workers and firms still exhibit higher productivity in treated locations, indicating long-lasting effects of highways. Moreover, these effects are accompanied by higher entry rates, suggesting that potential entrants also react to new transport infrastructure but take longer to respond.

We use a unified framework of economic geography with firm dynamics to theoretically decompose the benefits derived from improvements in transport infrastructure into two parts: gains resulting from reduced trade costs and gains stemming from local productivity growth driven by firm dynamics.

As is standard in static economic-geography models, our model features a country with a large number of locations (e.g., cities or municipalities) that differ in exogenous amenities and endogenous local labor productivity. These two characteristics, combined with the geography of trade costs, determine the spatial distribution of workers, wages, and outputs. The innovation of our model is that local productivity is the average of firms' productivities. Thus, local productivity is essentially determined by the number and composition of firms. Because firms' decisions about entry and exit are endogenous and dynamic, so is local productivity.

Our model highlights an important mechanism linking transport infrastructure, firm behavior, and local productivity. Suppose that the government builds a new highway to connect two important cities. Firms in locations along the road's path will benefit from greater market access. They will face lower trade costs, allowing them to sell their products in more distant markets and to lower prices for their goods. This boosts incumbent firms' size and profits, and therefore, their survival probability. Potential entrants observe the higher profitability of active firms, thus increasing the likelihood that new firms indeed enter. Crucially, the more productive and larger the firm, the higher its probability of entering and surviving. Thus, although the increase in market access benefits all firms regardless of their productivity, it reinforces the entry and persistence of large and productive firms. As a consequence, the productivity of locations along the new highway increases. The opposite is also the case; that is, the productivity at locations not connected by the new highway stagnates or decreases.

We recover model fundamentals through a combination of parameterization, model inversion, and internal calibration to match the sequence of spatial equilibria in the economic census from 1998 to 2018. We calculate the geography of trade costs by computing the minimum travel times between any pair of locations and parametrically mapping them to iceberg costs. We determine the path of amenities and labor productivity for all locations by inverting the system of spatial equilibrium equations. Finally, we recover the parameters governing the distribution of firm-level productivity and the entry and exit processes through internal calibration.

The calibrated model shows that new highways in Mexico from 1998 to 2018 contributed to real income and welfare growth, and that these benefits were unequally distributed. It reveals that firm dynamics played a central role in these effects. In line with the conclusions of previous, static studies (Allen and Arkolakis, 2014), our findings document that new highways increased welfare by 0.44% and increased aggregate real revenues by 0.64%; since Mexico invests annually 0.5% of its GDP in transport infrastructure, our results suggests that the policy is cost effective.

These aggregate effects hide substantial distributional effects. The areas that experienced the largest investments in new transportation infrastructure were in three key locations: those near the California and Texas borders, those close to the major ports serving Asia and Europe, and those close to the Caribbean Sea. In these locations, infrastructure improvements significantly reduced trade costs and improved market access, enhancing the relative competitiveness of firms that could tap these benefits. As a result, both real revenues and populations in these areas increased by nearly 10%, largely at the expense of the central regions of the country that were largely bypassed by highway infrastructure investments.

To understand how firm dynamics contributes to welfare and real income gains, we compare our baseline results to those from a model without firm dynamics – that is, one in which local productivity is exogenous and policy invariant. We find that productivity gains driven by firm dynamics explain up to 46% of the overall real income gains, and that the rest of the gains stem from reductions in trade costs. Moreover, in a model without firm dynamics, the dispersion of income gains is smaller, suggesting that firm dynamics are a force for spatial divergence.

Finally, we find that productivity grains are mostly driven by better firm selection. This finding comes from decomposing local productivity gains due to highways into two endogenous components: firm selection, as measured by average idiosyncratic firm productivity, and the number of firms. We find that the firm selection accounts for 77% of the productivity gains, and the increasing number of firms explains the remaining 33%.

Overall, our quantitative results show that new highways in Mexico had a more significant impact on the spatial reallocation of economic activity than on aggregate welfare and income. This finding conveys an important message to policymakers: transportation infrastructure can serve as a powerful tool for shaping the geographical distribution of economic activity by providing incentives for workers and firms to operate in specific locations.

Related literature and contributions

Our contribution is twofold. First, we offer new evidence on the effects of infrastructure on firm dynamics using panel data for all economic units in a developing country. Second, we develop a spatial general equilibrium framework where endogenous firm dynamics determine local productivity. In doing so, we establish a bridge between empirical research on the effects of infrastructure on firms and the dynamic spatial literature that quantifies the aggregate and distributional effects of place-based policies.

Economic geography. This paper builds on the work of Allen and Arkolakis (2014); Redding (2016); Allen and Arkolakis (2022). We extend their framework by incorporating firm dynamics. This approach endogenizes local productivity, allowing us to decompose the income and welfare gains resulting from new transportation infrastructure into two component parts: the reductions in trade costs, and the growth of local productivity.

Dynamic spatial models: Our paper relates to recent dynamic spatial frameworks. Using an approach similar to that of Caliendo et al. (2019), we present a model with trade and labor mobility; however, we allow for firm heterogeneity in a non-competitive market. Similar to the work of Lindenlaub et al. (2022), we focus on firms; using an approach similar to the one adopted by Kleinman et al. (2023), we also feature a dynamic spatial trade model with labor mobility. However, there are important differences in that Lindenlaub et al. (2022) abstract from the trade structure, and Kleinman et al. (2023) assume a representative firm by location with exogenous productivity. In contrast to both, we allow local productivity to be determined by the dynamics of heterogeneous firms in an internal trade environment. To the best of our knowledge, this is the first paper to incorporate entry, exit, and growth dynamics of heterogeneous firms in a spatial model with a realistic geography of trade costs, and then to validate it with a natural experiment.

Effects of infrastructure on growth. This paper also relates to the micro-empirical literature that measures the effects of transport infrastructure on local growth (Donaldson, 2018; Banerjee et al., 2020) and firm performance (Holl, 2016; Holl and Mariotti, 2018; Gibbons et al., 2019). Our contribution lies in providing new evidence for a developing country by using novel firm-level panel data that cover the universe of firms from all industries, both formal and informal, over a 20-year period. To the best of our knowledge, this is the first paper in this literature that features data of such comprehensive coverage for a developing country.

Furthermore, previous studies focusing on the effects of transport infrastructure on firm-level productivity have relied on traditional estimation procedures such as those used by Levinsohn and Petrin (2003) and Olley and Pakes (1992). However, these measures are based on value-added production functions and confound the effects of infrastructure on revenues and intermediate inputs. Our paper estimates firm productivity using a gross output-production function similar to that of Gandhi et al. (2020). This approach reveals productivity gains stemming only from higher revenues, in line with standard trade models.

Effects of infrastructure on firm dynamics. Evidence on the effects of infrastructure on firm dynamics is scarce because of data limitations. Among these few studies, Shiferaw et al. (2015) document that better transportation infrastructure favors firm entry, especially of large firms. Zhou (2023) also finds that locations with better exposure attract larger firms, but that places far from highways have higher entry rates. Our paper provides new evidence on entry and exit by documenting that responses to the arrival of new infrastructure are faster for exits than for entries. Moreover, our paper is the first one to show that while infrastructure does induce within-city firm migration, the entry and exit impacts of infrastructure are not the result of firms migrating across cities.

Effects of highways in the Mexican context. Other empirical studies have focused on the impacts of road infrastructure in Mexico. Examples include Durán-Fernández and Santos (2014); Pérez and Sandoval (2017); Blankespoor et al. (2017). These studies have relied on location-level data. By contrast, by exploiting panel identifiers from Busso et al. (2018), we show firm-level time variation for the first time. Moreover, our study examines the impacts of a more detailed and denser highway network, and it exploits execution of presidential construction plans as a source of exogenous variation to measure causal effects.

Structure of the paper. The rest of the paper proceeds as follows: Section 2 briefly discusses the economic and infrastructural context of Mexico. Section 3 discusses the sources, novelty and advantages of our data. Section 4 outlines our empirical approach and presents our results. Section 5 shows our dynamic spatial general- equilibrium model. Section 6 shows how we estimate the model and how the model fits the data. Section 7 presents our quantitative results. Section 8 concludes.

2 Growth and infrastructure in Mexico

After the implementation of macroeconomic policies inspired by the Washington Consensus in the 1990s and the North American Free Trade Agreement (NAFTA) in 1994, Mexico has enjoyed an extended period of macroeconomic stability (Levy, 2018). Nevertheless, in terms of real GDP, the nation has seen an average annual growth rate of merely 2.4% between 1995 and 2015, resulting in a corresponding annual growth of real GDP per capita of just 0.8%.

Economic growth has been not only slow but also unequally distributed across regions. Between 1995 and 2015, states near the US border, such as Chihuahua and Nuevo León, or in the central industrial belt such as Guanajuato and Querétaro, experienced rapid industrialization, resulting in annual real GDP growth rates exceeding 4%. Conversely, states in the southern region, such as Chiapas, Guerrero, and Oaxaca, remained largely underdeveloped and achieved an average real GDP growth rate of a mere 1% real over the same period.

A prevalent explanation for these disparities in economic performance is the unequal distribution of high-quality transport infrastructure. Regions with limited access to highways, railroads, and seaports are less appealing to firms that rely on high connectivity to intricate input-output networks (Dávila et al., 2002). In this perspective, highways are of unrivaled importance for Mexico, given that 83% of domestic cargo is transported via road freight.[1]

For the past two decades, the federal government has acknowledged deficiencies in the highways network and sought to address them through the sexennial National Infrastructure Plan. In these plans, the government determines the objectives, location, characteristics and budget of key, proposed highways. However, while most middle-

[1]In addition, 96% of people traveling within the country use highways.

income countries allocate between 1% and 5% of annual GDP to new, inland transportation infrastructure, Mexico's investment is only around 0.5% of GDP (OECD, 2020). As a result, Mexico's investments almost certainly insufficient to meet its transportation needs.

The extent to which this deficiency in robust transportation infrastructure might contribute to the country's sluggish economic growth, despite the implementation of ambitious macroeconomic reforms, continues to be a subject of ongoing debate. Moreover, it remains an open question as to whether a policy of more ambitious investments in road infrastructure in underdeveloped regions could potentially attract highly productive firms and reduce economic disparities across the country.

3 Data

Our study relies on three primary sources of data. The first is the Mexican Economic Census, which is conducted every five years. We rely on data collected from 1998 to 2018. These data have three important features: they cover the universe of establishments in Mexico, provide geolocations of establishments at the block level, and they longitudinally link establishments. These features allow us to characterize firms' dynamics across all locations. A second key data source is the National Highways Network. We use data from the network over the period from 2004 to 2019. These data allow us to determine all origin-destination travel times and to estimate trade costs between locations. A third key source of data is the National Infrastructure Plans from the presidential terms over the periods from 2007 to 2012 and 2013 to 2018. These plans describe how each new administration intends to spend its infrastructure budget. Here we provide next a brief overview of each data set's characteristics. (Greater details on data construction and cleaning procedures are provided in Appendix A.)

3.1 The Economic Census

Our main data source is the Mexican Economic Census, collected by the Mexican Institute of Statistics and Geography (INEGI). Although the census is conducted at the establishment level, throughout our paper we refer to these units as firms.[2] The census captures all formal and informal establishments of all sizes that produce goods or provide services in fixed facilities. The census includes such facilities in all locations with a population larger than 2,500 people and for all 6-digit industries according to the North American Industrial Classification System (NAICS). Excluded from the census are agriculture and government (and street vendors of any industry). In this paper, we focus on establishments in manufacturing, commerce, and service sectors. To leverage the panel structure of the census, we use INEGI's official firm identifiers to link the waves in 2008, 2013, and 2018. To link the waves 1998, 2003, and 2008, we use the fuzzy linkage described in Busso, Fentanes and Levy (2018), which uses firm identity, location, and industry to match units across census waves.[3]

Table 1 displays the coverage of the census, indicating that the number of firms increased from 2.7 million in 1998 to 4.7 million in 2018, representing an implied annual

[2] Levy (2018) documents that 99.7% of establishments are single-establishment firms.

[3] The accuracy rate of this linkage algorithm is 95% (Busso et al., 2018).

growth rate of 2.8%. Over the same period, the number of workers increased from 13.3 million to 24.8 million, with an implied annual growth rate of 3.1%. For reference, the corresponding average GDP growth rate was 2.4%.

Table 1: Mexico's Economic Census

Year	**Firms** (millions)	**Workers** (millions)	**6-digit sectors**	**Populated locations**
1998	2.72	13.31	720	2,566
2003	2.92	14.41	726	2,629
2008	3.66	18.14	732	2,801
2013	4.17	19.66	735	3,033
2018	4.73	24.82	741	3,234

Notes: Full census coverage.

Based on annual employment surveys, there were an estimated 39 million workers in urban the locations that were included in the 2018 economic census, (i.e., places with more than 2,500 people). Table 1 reveals that our data encompass almost 25 million workers, representing 61.5% of the national workforce. The difference between these figures is due to the government sector, which employs 4 million workers, and the remaining 10 million workers who operate as street vendors.[4]

Locations. The Economic Census stratifies the territory into three primary levels: state, municipality, and locality. While the boundaries and codes for states and municipality remain constant, those for localities may change because they are based on demographic characteristics that may require redefining a given census tract's boundaries. To account for differences in census tracts, we establish our own fixed geography. We accomplish this by defining a time-consistent set of locations, composed of localities likely to belong to the same city. The procedure consists on generating a 1 km buffer around the 7,136 localities and classifying contiguous buffers as the same location. This procedure results in 3,248 locations consistent across all census waves. Panel (a) in Figure 1 shows their geographic distribution.[5]

3.2 The National Highways Network

The second data source is the National Highways Network (*Red Nacional de Carreteras*). This database, published by INEGI, consists of shapefiles including all national and state paved roads and highways in Mexico at five points in time: 2004, 2011, 2014, 2018, and 2019. Panel (b) in Figure 1 illustrates this network in 2018. In 2004, Mexico had 106,079 kilometers of paved highways, by 2019, the network reached 187,453 kilometers. [6]

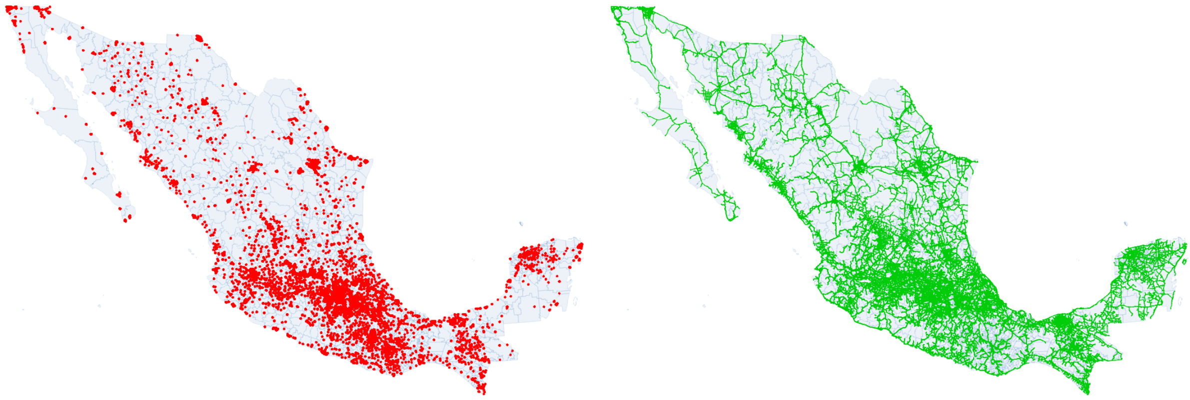
We use the data on highways to create a matrix of minimum travel times between any two locations in the country to help estimate internal trade costs for our quantitative

[4]Table 1 also shows that the number of 6-digit sectors slightly increased from 720 6-digit industries in 1998 to 741 in 2018. This is mostly due to revisions of the NAICS.

[5]Table 1 shows that the economic census increases its geographic coverage over time. The main reason is that, as the population grows, more localities cross the 2,500-person threshold, and thus they qualify to appear in the economic census.

[6]The comparable network in France is close to 1 million kilometers (*Autoroutes nationales, départementales et communales*). To put this into perspective, France at that time had 14 meters of highway per capita, 10 times the 1.4 meters per capita figure for Mexico..

Figure 1: Locations and highways network in Mexico, 2018



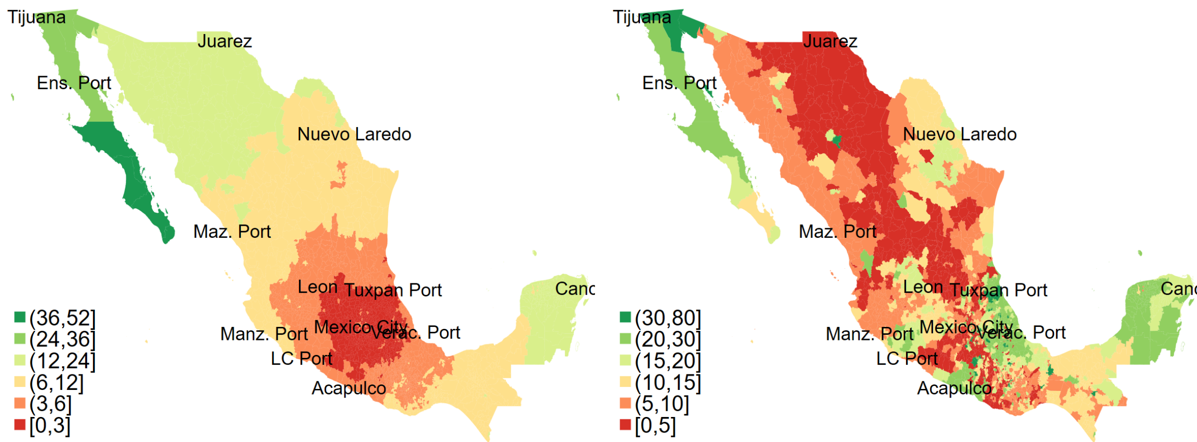
(a) 3,248 locations

(b) 187,000 km of highways

Notes: Panel (a) shows locations following our definition. Panel (b) all paved roads and highways excluding within-city roads.

model. With 3,248 locations defined, the size of our minimum-travel-times matrix is 3,248×3,248. To compute it, we implement the Dijkstra (1959) algorithm, which finds the shortest path between two nodes in a network. We reduce the digitization bias pointed out by Allen and Arkolakis (2014), by discretizing the space into a grid of 382,181 hexagons.[7] Each hexagon is weighted by the maximum legal speed on the highways that cross them. If two or more highways cross a hexagon, we use only the highway with the top maximum speed. If a hexagon belongs to the interior of a city, we assume that its speed is 30km/h. Hexagons carry information about how level or steep the terrain is; this is considered in the computation. (Appendix A provides additional details.)

Figure 2: Estimated minimum driving times to Mexico City



(a) Estimated minimum number of hours needed to drive from municipalities to Mexico City (2018)

(b) % decrease in estimated minimum number of hours to drive from municipalities to Mexico City (1998-2018)

Notes: Maps subdivided into municipalities.

[7]The edge length is 1.22 kilometers. The H-resolution is 7 according to Uber's Hexagonal Hierarchical Spatial Index.

Panel (a) of Figure 2 shows the minimum travel times required to drive to Mexico City from the 2,457 other municipalities in the country. Assuming no traffic jams, 70% of municipalities can be reached from Mexico City within 6 hours; 20% take between 6 hours and half a day, and the remaining 10% require at least half a day. The most remote location is a 52-hour drive from Mexico City.

Panel (b) of Figure 2 illustrates the percentage change in time required to reach Mexico City during the period 1998-2018. The time needed to reach Mexico by road decreased by less than 10% over that period. For nearly one-third of Mexico's municipalities the time needed to reach the capital declined by 10% and 20%. For roughly one-fifth of the municipalities, the time needed to drive to the capital decreased by more than 20%. The regions that saw the most significant improvements, shown in green on the map, include those near the Caribbean Sea, the California and Texas ports of entry, and the two primary seaports connecting the country to Europe and Asia.

3.3 The National Infrastructure Plans

Our third data source is the National Infrastructure Plans. These data contain 250 construction plans from 2007 to 2018. They provide a source of quasi-natural variation that we utilize in our empirical analysis. The plans originate from two distinct presidential terms: 175 from the Felipe Calderón administration (2007-2012) and 75 from the Enrique Peña Nieto administration (2013-2018).

We use geographical software to locate all 250 plans on a map. If plans are executed, their locations can be easily pinpointed on a map since they appear in subsequent waves of the highway network shapefiles with updated characteristics. However, in cases where the plans are not executed, we infer their locations based on the plan descriptions. Subsequently, we draw these hypothetical highways on our shapefiles and assign them attributes such as width, number of lanes, and maximum speed based on the technical specifications provided in the construction plans.

To accurately document plans' execution and timing, we relied on annual progress reports from the Mexican Transportation Ministry to Congress. These reports provide detailed information on the number of kilometers built each year, the amount of money spent, and the year of project completion. It is important to note that highway construction plans may or may not be executed for various reasons. The actual execution of a project could be influenced by budgetary changes, technical challenges, opposition from the local population, or other political considerations. Unfortunately, the reports do not specify the reasons why a given plan was not built. In the empirical section, we examine whether plan execution and timing can be predicted by the characteristics of adjacent cities.

Table 2 presents the execution status of the construction plans and their timing. For the administration over the period from 2007 to 2012, 40% of the 175 construction plans were fully executed. Half of these plans were completed within the first four years of the presidential term, while the remaining half were finished in the last two years. Similarly, for the administration over the period from 2013 to 2018, 56% of the 75 construction plans were completed, with half of them being finished in the first 2 years.

Table 2: Construction plans and year of execution

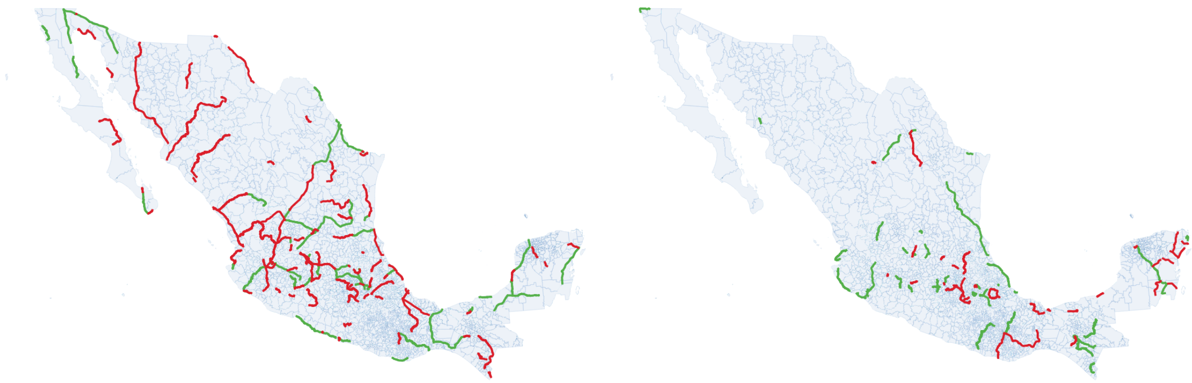
(a) 2007-2012 Administration

Executed	Execution year	Total
No		115
Yes	2007	2
	2008	11
	2009	9
	2010	7
	2011	10
	2012	21
Total		175

(b) 2013-2018 Administration

Executed	Execution year	Total
No		33
Yes	2013	9
	2014	10
	2015	4
	2016	9
	2017	10
Total		75

Figure 3: The construction plans.

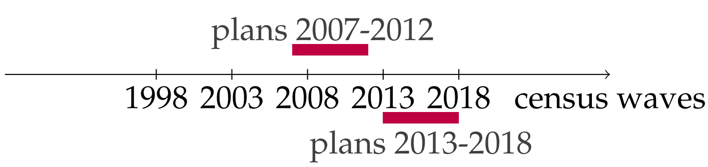


(a) Plans 2007-2012 (b) Plans 2013-2018

Notes: Green lines denote construction plans that were completed. Red lines denotes plans that were not built.

Figure 3 shows the geographical distribution of plans according to their execution status. The majority of states were crossed by at least one plan during the first administration. In contrast, most plans during the second administration were concentrated in the southern region of the country.

Figure 4: Overlap construction plans and Economic Census waves



We combine these construction plans with economic census data. As shown in Figure 4, there is no perfect temporal overlap between the two databases. We leverage this fact to characterize pre-treatment, treatment, and post-treatment periods. Clearly, the censuses in 1998 and 2003 serve as pre-treatment periods for both sets of construction plans, and the censuses from 2008 to 2018 serve as staggered treatment periods.

4 Empirical evidence

We document how improvements in transportation infrastructure affect local labor productivity and firm dynamics. We first combine data from the Mexican Economic Census with information from the National Highways Network, and then leverage the timing of the execution of presidential construction plans as a source of plausibly exogenous variation to estimate a staggered differences-in-differences regression model, as in Callaway and Sant'Anna (2021).

Measuring the effects of infrastructure on economic outcomes is a challenging task for two main reasons. First, the placement of infrastructure projects is not random; most of the time, economic or political considerations motivate the placement. Second, infrastructure projects, such as highways, may produce spillover effects because such projects are part of a larger network that can benefit all locations to varying degrees. Our empirical approach explicitly addresses the first problem. However, in our baseline specification, we do not account for spillover effects. If spillovers do exist, our estimates would represent a lower bound.[8]

4.1 Main specification

The main goal of our empirical section is to document that when firms are exposed to better transport infrastructure, their performance improves, and so do their chances of entering and surviving. Moreover, we are interested in disentangling whether these effects stem from the actual construction or simply the announcement of new highways. Finally, we aim at determining if highways have only a temporary effect on firms or if they persist in the medium-run. To capture these effects we rely on a standard differences-in-differences model with staggered treatment timing. The regression equation is of the form:

$$y_{n,i,t} = \alpha_i + \alpha_t + \gamma' \mathbf{X}_{n,i} + \sum_{e=1}^{min} \beta_e^{persist.} \cdot D_{i,t-e} + \beta_0 \cdot D_{i,t} + \sum_{e=1}^{max} \beta_e^{anticip} \cdot D_{i,t+e} + \varepsilon_{n,i,t} \quad (1)$$

In (1), the index n denotes the firm, i denotes the location, and t denotes the period. On the left-hand side, $y_{n,i,t}$ represents the outcome of interest. On the right-hand side, the coefficient α_i indicates location and α_t corresponds to time fixed effects. $\mathbf{X}_{n,i}$ is a vector of observed control variables. The error term ε_{it} is clustered at the location level, at which the treatment occurs as is standard in the literature.

The treatment variable, D_{it}, is defined at the location level i. It is a binary indicator that takes the value of one for firm n if its location is exposed to the execution of a construction plan at time t and zero otherwise. The model includes three conceptually different treatment effects. The set of coefficients $\beta_e^{persist.}$ captures the effects of the treatment before period t on current outcomes. The coefficient β_0 measures the contemporaneous treatment effect at t. Finally, the set of coefficients $\beta_e^{anticip.}$ reflects possible anticipatory effects at t of future treatments. We provide a detailed description of D_{it} below.

[8]We are working on a robustness check to account for spillover effects by specifying counterfactual infrastructure shocks as in Borusyak and Hull (2020).

For the coefficients $\beta_e^{persist.}, \beta_0, \beta_e^{anticip.}$ to be identified, the model relies on the following assumptions. The first concerns the *irreversibility of the treatment*; that is, once a highway is built, it cannot be destroyed. This assumptions ensures that the three groups of coefficients are separately identified. The second concerns *conditional parallel trends* based on a never-treated group; that is, only firms in a location with the same characteristics would follow the same trend in the absence of treatment. This assumption guarantees that the measured effects can have a causal interpretation. Following Theorem 1 in Callaway and Sant'Anna (2021), these assumptions imply that we can identify all group-time average treatment effects (ATE).

4.2 Outcomes

In this section we provide a detailed definition of our outcomes of interest: value added per worker, firm-level total factor productivity (TFP), firm size, and firm entry and exit rates.

Value added per worker. We calculate this by dividing firm value added by the number of workers. Value added is defined as the total revenue derived from all commercial activities of the firm, minus intermediate expenditures, such as raw materials and electricity. The definition of total workers includes blue- and white-collar employees, as well as owners, outsourced personnel, and piece-rate workers. We represent this metric logarithmically as $log(VA/L)$. This measure offers the advantage of being consistent with models that use standard frameworks in which the production function is constant returns to scale, and it relies solely on labor.

Revenue productivity. We measure TFP as in Gandhi et al. (2020) (henceforth GNR). This measure assumes a Cobb-Douglas production function of the form $y = TFP \cdot k_s^{\alpha} l_s^{\beta} m_s^{\gamma}$, where y represents gross output, k is the capital stock, l is total workers and m is the intermediate inputs. The three input elasticities, $\alpha_s, \beta_s, \gamma_s$, are assumed to be the same for all firms within the same three-digit industry s. We express this outcome logarithmically as $log(TFP)_{GNR}$. The main advantage of this productivity measure is that it attributes all increases in TFP to higher revenues while holding inputs constant. Traditional value added-based production functions such as Olley and Pakes (1992); Levinsohn and Petrin (2003); Ackerberg et al. (2015) cannot disentangle whether an increase in TFP is due to higher revenue or reductions in intermediate input expenditures. It is important to note that $log(TFP)_{GNR}$ is a revenue productivity measure. This means that it cannot disentangle whether a higher TFP is due to an increase in prices or an increase in physical productivity. This issue can be solved by exploiting firm-level prices; unfortunately, such data are unavailable in the Economic Census.

Firm size. This is simply the sum of all blue- and white-collar workers, owners, and outsourced and piece-rate workers. We denote this outcome in logs as $log(L)$. We consider owners and family members as part of production workers since most firms in Mexico operate exclusively with type of workers in profit-sharing agreements.

Average wage. This is measured as the total wage bill divided by the number of workers. We express this outcome in logarithms as $log(w)$. In cases in which firms do not report the wage bill because they operate under profit-sharing agreements that are commonly used by most informal firms we employ the wage imputation method described in Busso et al. (2012). This procedure involves assigning missing wages to be the same as those in firms from the same state, six-digit industry, and of similar size.

Entry and exit. For entry, this is a dummy variable that takes the value of one if the firm appeared for the first time in the census wave, and zero otherwise. For exit, it takes the value of one if the firm is observed for the last time and zero otherwise.

4.3 Treatment and sample

Treatment. The treatment variable, denoted as $D_{i,t}$, is an index function that equals one if the firm operates close to a fully executed construction plan and zero otherwise. A location is considered to be close to a construction plan if it overlaps with a buffer of radius B around the plan. For robustness checks, we consider different values for B, specifically, 5, 10 and 15 kilometers.

Figure 17 in Appendix B illustrates treated (in green) and not-yet-treated (in red) locations for a specific buffer size B. Notice that the treatment is not defined for locations that do not overlap with any buffer; this will affect the sample size.

Sample. The sample includes only locations overlapping with construction plans. Table 3 shows the number of locations in the sample for $B = 5$ kilometers. It shows that 771 of the 3,248 locations overlap with construction plans from 2007 to 2012. Among them, 259 intersect with plans that were fully executed before 2012, and another 512 intersect with plans that were not undertaken. Similarly, for the construction plans envisioned over the period from 2013 to 2018, 457 locations overlap with construction plans; among them, 278 were fully executed before 2018. Table 14 in the appendix shows how the number of locations in the sample increases when we use a larger buffer size.

Table 3: Locations in sample and treatment group

Plans period	**2007-2012**	**2013-2018**
With plans	771	457
With out plans	2,475	2,789
Total locations	**3,246**	**3,246**
Executed	259	278
Not executed	512	179
Total locations	**771**	**457**

Although the Economic Census covers from 2.7 million firms in 1998 to 4.7 million in 2018 (see Table 1), we do not include all of them in our empirical estimation. Our sample is limited to firms in locations overlapping with construction plans. For instance, considering the construction plans from 2013 to 2018, Table 4 shows that 2.73 million firms in 2018 are in the sample. Among them, 1.26 million are in the treatment group. Table 15 in the appendix shows how the number of firms in our sample increases as we increase the buffer size.

Table 4: Firms in the sample and treated group

Plans period	**2007-2012**		**2013-2018**	
Census	Sample	Treated	Sample	Treated
1998	2.09	1.43	1.65	0.73
2003	2.23	1.51	1.75	0.77
2008	2.72	1.82	2.14	0.97
2013	3.06	2.04	2.43	1.12
2018	3.43	2.26	2.73	1.26

Notes: Treated means that the firm belongs to the treatment group, not that it was treated at that period.

4.4 Validity

The validity of our empirical approach relies on the timing of execution of construction plans being orthogonal to economic outcomes. We provide three tests to show that this source of variation is indeed as good as random.

The first test evaluates whether execution of plans can be predicted. We show that while the geographical assignment of construction plans is correlated with demographic, economic, and political characteristics, the actual execution and the timing is not. To do this, we regress, at the location level, an index variable denoting if a location is close to a construction plan, and whether it was executed, on local characteristics. Column (1) from Table 16 (Appendix B) shows that certain areas are more likely to be targeted by a construction plan. These areas are those that have larger populations and higher value added per worker, and those that voted for the opposition party in the previous presidential election. Column (2), however, shows that none of these characteristics matter for the eventual execution of the plan.

The second test provides a balance table to study whether treated and untreated locations differ in characteristics at baseline. We find that although there are some differences in levels, there are none in growth rates. Table 17 (Appendix B) shows that treated and untreated groups are similar in population, average firm size, average firm productivity, and industrial composition. Firms in treated locations, however, hire more formal workers on average, and they are more capital intensive. If we focus on growth rates, they don't seem to evolve differently, which suggests that existing differences are constant across time.

The third test addresses whether the parallel-trends assumption holds. As we show in the following section (tables 5 and 6), there are no statistically significant pre-trends in our outcomes of interest.

Additional concerns about the validity of our approach are that construction plans may only capture minor improvements in the highways network, and that most of the effects that we measure may be driven by other infrastructure projects tied to the plans, such as industrial parks or housing developments. In Table 18 (Appendix B) we provide evidence that the construction plans have a significant effect market access. Execution of construction plans imply an increase in market access of 0.07%. Because the baseline increase was on average 0.13%, the implied gains derived from plan execution are 53%.

4.5 Empirical results

To derive our baseline results we estimate two separate event-study models following Callaway and Sant'Anna (2021). One is for the 2007-2012 construction plans, and the other is for the 2013-2018 plans. Regressions are estimated at the firm level, assuming that the data are repeated cross-sectional.

Tables 5 and 6 show our baseline results for a buffer size $B = 5$km. As is good practice in the literature (Baker et al., 2022), we show first our estimates without covariates. Appendix B shows robustness checks that include firm- and location-level covariates; we separately estimate the model for tradable and non tradable goods, and for different buffer sizes.

Table 5: Baseline results. Construction plans 2007-2012

	(1) $log(va/L)$	(2) $log(TFPR)_{GNR}$	(3) $log(L)$	(4) $log(w)$	(5) $Entry$	(6) $Exit$
β_{-1}	-0.0167	-0.0041	-0.0014	-0.0059	0.0083	0.0074
s.e.	[.0228]	[.0135]	[.0084]	[.0056]	[.0069]	[.0072]
β_0	-0.0017	0.0044	-.0139**	-0.0015	0.0143	-.0169**
s.e.	[.0158]	[.0056]	[.0063]	[.0057]	[.0101]	[.007]
β_1	.0653***	.0174**	-0.0049	-.0111**	.0158***	-.0329**
s.e.	[.0197]	[.0082]	[.0098]	[.0054]	[.0053]	[.0129]
Controls	No	No	No	No	No	No
Obs.	7,060,649	7,060,649	7,060,649	7,060,649	7,060,649	7,060,649

Notes: Standard errors are in brackets. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$. The sample includes all firms from 1998 to 2018. It excludes firms with value added or capital levels smaller than zero.

Construction plans 2007-2012. Table 5 shows that, for all outcomes of interest, β_{-1} is not statistically different from zero, which suggests that firms did not react to the treatment before they were exposed, and thus, that the parallel-trends assumption holds. According to the estimated β_0, there is no evidence of a contemporaneous effect of construction plan execution on labor productivity and firm TFP. There is a negative effect on firm size, but this does not have a significant effects on wages. Though there are no contemporaneous effects on firm entries, there are effects on plan exits; plan execution decreases firm exits by 1.69 percentage points. Finally, the coefficients β_1 capturing effects of highways five years after their construction, show a 6.5% increase in labor productivity and a 1.74% increase in firm TFP. Firm size is not affected. Wages slightly decrease. Firm entries increase by 1.6 percentage points, and firm exits decrease by 3.3 percentage points.

In summary, although the results for the 2007-2012 construction plans are in line with a story of labor and firm productivity gains and changes in firm dynamics due to better transport infrastructure, the results also suggest that these effects may take time to unfold.

Construction plans 2013-2018. Table 6 shows that there are no anticipatory effects for all outcomes of interest, except one, $log(va/L)$. The estimates for β_0 suggest significant contemporaneous effects on productivity and firm dynamics. When construction

Table 6: Baseline results. Construction plans 2013-2018

	(1) $log(va/L)$	(2) $log(TFPR)_{GNR}$	(3) $log(L)$	(4) $log(w)$	(5) $Entry$
β_{-1}	-.0641**	-0.0073	-0.0028	0.002	0.0086
s.e.	[.0257]	[.0075]	[.0076]	[.0048]	[.0055]
β_0	.0547**	.0179**	.0157*	.0113**	0.0018
s.e.	[.0226]	[.0074]	[.0092]	[.005]	[.0079]
β_1	-0.0013	0.0094	.0335***	.0146**	.0238*
s.e.	[.0231]	[.0112]	[.0109]	[.0065]	[.0124]
Controls	No	No	No	No	No
Obs.	6,375,668	6,375,668	6,375,668	6,375,668	6,375,668

Notes: Standard errors are in brackets. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$. The sample includes all firms from 2003 to 2018. The sample excludes firms with value added or capital levels smaller than zero.

plans are executed, local labor productivity increases by 5.5%. This increase is coupled with an 1.8% rise in firm TFP and a 1.6% increase in firm size. There is a positive but noisy effect on average wages. There is no effect on firm entry.[9] One period after the treatment – that is, five years – neither workers nor firms in treated locations continue to be more productive. However, they become even larger (3.3%), and firm entry increases by 2.4 percentage points.

In summary, the results for 2013-2018 construction plans are in line with our hypothesis that better transportation infrastructure increase local labor productivity and that this is linked to more productive firms and changes in firm dynamics, notably, higher survival and entry rates. Although the effects on productivity are not persistent, effects on firm dynamics are.

4.6 Robustness checks

Regressions by sector. In Appendix B we show the results estimated separately by three broad sectors: manufacturing, commerce and services. Table 19 shows the results for the 2007-2012 construction plans. The contemporaneous negative effects of highways on exit are present in all sectors although they are stronger in manufacturing and services (2 percentage points) than in commerce (1.4 percentage points). As in the aggregate case, the effects on productivity and firm dynamics appear one period after the treatment. The largest increases in labor productivity (8.4%) and firm TFP (3.6%) are in the commerce sector. Higher entry rates are present only in the services sector and lower exit in all. Overall, the sector that has the strongest response to new transportation infrastructure is commerce. This is not surprising since this is the sector for which trade costs are more relevant for input and output markets.

Table 20 shows the results for the 2013-2018 construction plans. Results by sector show that the contemporaneous positive effects on productivity are driven mostly by the commerce and services sectors and not by manufacturing. Again, there are no con-

[9] Exit is not defined for this regression as the Census 2023 was not yet available at the time of this writing.

temporaneous effects of firm entry. One period after the treatment, there are negative effects on revenue productivity for manufacturing firms, no effects for commerce, and positive effects for services. Higher entry five years after the treatment is only present in the commerce sector.

Controls. Tables 21 and 22 in Appendix B show that our results are robust to adding time-invariant controls that take the Economic Census 1998 and the Population Census 2000 as baseline. For the 2007-2012 construction plans, point estimates preserve the sign, are slightly larger, and increase their statistical significance. A similar pattern is observed for the 2013-2018 construction plans.

Different buffer sizes. Tables 23, 25, 24 and 26 in Appendix B show that our results are robust to larger buffer sizes. Focusing on the 2013-2018 construction plans, as the buffer size increases, most point estimates decrease and some become statistically zero. This is consistent with the fact that as we increase the buffer size, we also increase the sample and the risk of considering more distant locations as treated when they are only weakly affected by the construction plans.

Firm mobility. A common source of bias when studying firm entry and exit is firm relocation. When relocations are not tracked in the data, address changes are counted as an exit and then recounted as a new entry, biasing both rates upwards. Since we can track firm location changes across the entire country in the census, we verify whether new transport infrastructure incentivizes firms to relocate. In Appendix B we show that although firm relocation can be substantial, as much as 5% of all surviving firms, they mostly move within a given city or commuting zone; thus, this does not bias our results because our treatment is defined at the location level. Interestingly, we find that new transport infrastructure does affect within-location firm relocation.

4.7 Discussion

Our findings have shown that new transport infrastructure has a positive effect on local labor productivity, and that this increase is associated to an increase in firm TFP. The positive effects of infrastructure on firm-level productivity we find are in line with those of previous findings (Holl, 2016; Holl and Mariotti, 2018; Gibbons et al., 2018). Labor and firm productivity may increase for many reasons. For example, average firm TFP can stem from better firm selection or from agglomeration externalities (Combes et al., 2012). Wan and Zhang (2017); Lee (2021); Xu and Feng (2022) provide empirical evidence that new highways incentives firm agglomeration, and Ahlfeldt and Feddersen (2018) find that infrastructure is a driver of better firm selection. Though our empirical study cannot disentangle selection from agglomeration effects, our evidence on firm entry and exit suggest that firm selection plays an important role in the overall increase in productivity.

The findings also show that new infrastructure affects firm dynamics – that is, it impacts the processes of firm entry, exit, and growth. The literature has found mixed evidence regarding infrastructure's impacts on the entry process. Audretsch et al. (2017); Gibbons et al. (2019) find that the number of firms in places with better access to infrastructure increases, mostly driven by entry; however, Chang and Zheng (2022) find no effects on entry and a decline in the number of firms in locations exposed to new transport infrastructure. In general, we do not find statistically significant effects on entry in the short run. However, we find positive effects one period after the treatment (five years later). Research documenting the effects of transport infrastructure on firm exit is scarce. We find negative effects of new highways on firm exit, which is consistent with a story in which better highways decrease trade costs and increase firm profitability and chances of survival.

In the following section, we propose a model that rationalizes why new transportation infrastructure distorts firm dynamics, and how this mechanism determines location-level productivity. In the model, local labor productivity is directly determined by the composition for firms; thus, firm selection is an important channel that drives the effects of better infrastructure on economic outcomes. Although we do not model agglomeration forces directly, the model is flexible enough to account for them at no computational cost (as described in Appendix C).[10]

5 Model

In Section 4, we documented that new highways increased firm-level TFP, firm entry, and the likelihood of a firm's survival. These positive effects translate into higher local labor productivity. In this section, we outline a theoretical framework that allows us to interpret these results and study the implications for aggregate output, welfare, and the spatial distribution of economic activity. To do this, we build upon an economic geography model à la Allen and Arkolakis (2014) to incorporate firm dynamics by which we mean the endogenous processes of entry, exit, and growth of heterogeneous firms in the tradition of Melitz (2003).

5.1 Geography

Time is discrete and indexed by t. In each period, there exists a fixed set of locations in the country denoted by $\mathcal{J} = 1, 2, \ldots, J$.[11] Locations in this economy are understood as local labor markets such as cities or commuting zones. They are interconnected by a network of highways that can be improved by building new routes or upgrading existing ones. Improvements in the highways network can reduce the minimum travel times between any two locations.[12] We denote the matrix of minimum travel times between locations i and j as $\{T_{i,j,t}\}_{i,j\in\mathcal{J}}$.

We assume that the matrix of minimum travel times is sufficient to determine a geography of bilateral trade costs, denoted by $\{\tau_{i,j,t}\}_{i,j\in\mathcal{J}}$.[13] For now, we remain agnostic about the exact function that maps travel times to trade costs. From now on, for all variables with subscript (i, j), (i) denotes the origin, and (j) denotes the destination.

[10]The main challenge is identification. It is seldom straightforward to disentangle the parameter governing agglomeration externalities from baseline productivity.

[11]For endogenous city formation see Gaubert (2018).

[12]We rule out the Braess's paradox stating that adding one or more roads to a road network may slow down overall traffic flow through it. A paper featuring congestion is Allen and Arkolakis (2022).

[13]This assumption is reasonable in the absence of internal tariffs.

5.2 Households

At time t, the country is inhabited by an exogenous number of perfectly mobile households, denoted as $\bar{L}_t$. Households decide where to reside and how much to consume. Each household is endowed with one unit of labor, which is inelastically supplied to the local labor market at a wage rate of $w_{i,t}$. The household consumes a basket of varieties $c_{j,i,t}(n)$ produced by firm n in location j. These varieties form a composite good $C_{i,t}$ aggregated à la Dixit and Stiglitz (1977):

$$C_{i,t} = \left[\sum_{j \in J} \sum_{n \in M_{j,t}} c_{j,i,t}(n)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{2}$$

Where $\sigma > 1$ is the elasticity of substitution across all varieties. The price of a variety $c_{j,i,t}(n)$ is denoted by $p_{j,i,t}(n)$. Utility is derived from this basket of goods and local amenities $u_{i,t}$ according to the function:

$$U_{i,t} \equiv C_{i,t} \cdot u_{i,t} \tag{3}$$

Amenities rationalize why households move to certain places despite receiving lower wages. These considerations include good weather, cultural attractions, family ties, and birthplace preferences (Zerecero, 2021). The consumption basket $\{c_{j,i,t}(n)\}$ maximizes (3) subject to the budget constraint:

$$\sum_{j \in J} \sum_{n \in M_{jt}} p_{j,i,t}(n) c_{j,i,t}(n) = w_{i,t} + d_{i,t} \tag{4}$$

Where $d_{i,t}$ denotes the dividends paid by the firms to households. We assume that all profits are collected by a central fund and then redistributed. Using the approach undertaken by Chaney (2008), each household owns $w_{i,t}$ shares of the fund, thus, income is proportional to the local wage and does not affect household's location choices. For the sake of simplicity in notation, we omit dividends from the equations.[14]

From the household's utility-maximization problem we can show that the instantaneous, indirect utility depends on the real wage $\frac{w_{i,t}}{P_{i,t}}$ and local amenities $u_{i,t}$ as follows:

$$U_{i,t} = \frac{w_{i,t}}{P_{i,t}} \cdot u_{i,t} \tag{5}$$

Where $P_{i,t}$ is the standard price index of location i, defined as:

$$P_{i,t} \equiv \left[\sum_{j \in \mathcal{J}} \sum_{n \in M_{j,t}} p_{j,i,t}(n)^{1-\sigma} \right]^{\frac{1}{1-\sigma}} \tag{6}$$

Aggregate Marshallian demand of the $L_{i,t}$ households in location i for a variety n pro-

[14]Under this assumption, we can show that the actual income is $\frac{\sigma}{\sigma-1} w_{i,t}$ which proportionally shifts welfare $U_{i,t}$ for all i.

duced at location j is:

$$c_{j,i,t}(n) = p_{j,i,t}(n)^{-\sigma} w_{i,t} L_{i,t} P_{i,t}^{\sigma-1} \tag{7}$$

According to this demand function, the price elasticity is σ and $w_{i,t}L_{i,t}P_{i,t}^{\sigma-1}$ is a local demand shifter that proportionally raises demand for all local varieties. The demand function implies that households demand a positive amount of all varieties as long as there exists a firm willing to produce them.[15]

Households' location choice. Households are freely mobile and decide where to live at the beginning of every period. The value of living at location i at time t is:

$$W_{i,t} = U_{i,t} + \beta \mathbb{E}_{\Omega} \left[W_{t+1} | \Omega_t \right] \tag{8}$$

Where Ω_t is the aggregate state of the economy at time t, which includes all information about the distribution of prices and quantities across locations. Households discount the future at rate $\beta \in (0, 1)$ forming beliefs $\mathbb{E}_{\Omega}$ through expectations that may depart from rational. The continuation value is W_{t+1}, defined as:

$$W_{t+1} = \max_{j \in \mathcal{J}} \{ W_{j,t+1} \} \tag{9}$$

The absence of a moving cost in the continuation value reflects the fact that households can freely move from location i to j. The location choice is then:

$$i = arg \max_{j \in \mathcal{J}} W_{j,t} \tag{10}$$

5.3 Firms

Technology. In period t, there are $M_{i,t}$ heterogeneous, risk-neutral firms at location i. They use labor to produce a single variety, indexed by $n \in M_{i,t}$, with the following constant returns to scale technology:

$$y_{i,t}(n) = \psi_{i,t}(n) \cdot l_{i,t}(n) \tag{11}$$

Where firm-level productivity, $\psi_{i,t}(n)$, is separable in two parts as:

$$\psi_{i,t}(n) = z_{i,t} \cdot s_i(n) \tag{12}$$

Where $z_{i,t}$ is a random location-specific productivity shifter.[16] It rationalizes why the same firm would exhibit different labor productivity when situated in a different location or when experiencing distinct time periods. On the other hand, $s_i(n)$ is the idiosyncratic productivity of a firm, which is time invariant and drawn before entry.

Profit maximization. Firms operate in a monopolistic competition market and sell

[15] It is straightforward to extend this framework to many sectors as in Asturias et al. (2019). This will imply having different elasticities within and across sectors. Arkolakis et al. (2019) show that heterogeneous markups may imply smaller welfare gains from trade.

[16] This shifter can be further decomposed by making assumptions on, for instance, agglomeration externalities (Combes et al., 2012).

their products to all locations. When firm n in location i serves market j, it chooses labor, output, and prices to solve:

$$\max_{p_{i,j,t}(n),y_{i,j,t}(n),l_{i,j,t}(n)} \pi_{i,j,t}(n) = p_{i,j,t}(n)y_{i,j,t}(n) - w_{i,t}l_{i,j,t}(n) \qquad \forall j \in \mathcal{J} \qquad \text{subject to} \quad (7) \tag{13}$$

Consumers at j pay $p_{i,j,t}(n) = \tau_{i,j,t} \cdot p_{i,t}(n)$, where $p_{i,t}(n)$ is the price at the location of origin. At the optimum, firms will price a constant markup over the marginal cost. That is:

$$p_{i,j,t}(n) = \left(\frac{\sigma}{\sigma - 1}\right) \frac{\tau_{i,j,t}w_{i,t}}{\psi_{i,t}(n)} \tag{14}$$

Optimal labor and quantities follow from (14) and the demand and production functions. Equation (14) implies that all differences in prices of the variety n are fully explained by differences in trade costs; so any reductions in trade costs will be fully passed on to consumers in the form of a lower price.

Definition 1. *Location's i **market access** is:*

$$ma_{i,t} \equiv \tilde{\sigma} \sum_{j \in \mathcal{J}} \tau_{i,j,t}^{1-\sigma} w_{j,t} L_{j,t} P_{j,t}^{\sigma-1} \tag{15}$$

where $\tilde{\sigma} \equiv \left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma}$.

Proposition 1. *Firm's (total) optimal labor demand and profits are:*

$$l_{i,t}(n) = \psi_{i,t}(n)^{\sigma-1} \cdot w_{i,t}^{-\sigma} \cdot ma_{i,t} \tag{16}$$

and

$$\pi_{i,t}(n) = \frac{1}{\sigma} \cdot \psi_{i,t}(n)^{\sigma-1} \cdot w_{i,t}^{1-\sigma} \cdot ma_{i,t} \tag{17}$$

Proof. See Appendix C. □

According to (16) and (17) static optimal decisions of firms depend only on their productivity, local wages, and market access.[17]

Incumbent's problem. Firms decide to stay or exit after production takes place and profits are realized. The value of an incumbent firm in location i producing variety n is:

$$V_{i,t}(n)^I = \pi_{i,t}(n) + \beta \mathbb{E}_{\Omega} \left[V_{i,t+1}(n)|\Omega_t\right] \tag{18}$$

Where the continuation value, normalizing the outside option for entrepreneurs to zero for all n, is:

$$V_{i,t+1}(n) = \max\{V_{i,t+1}(n)^I - f_{i,t}(n), 0\} \tag{19}$$

Here, $f_{i,t}(n)$ is a random operating cost drawn at the end of period t. This operating cost provides the rationale that can explain why there is not a hard productivity cut-off

[17] Firms have no local labor market power; thus they take wages and market access as given. See Azkarate-Askasua and Zerecero (2022) for local labor market power.

for exiting firms in the data; some productive firms exit, and some unproductive firms stay in the market.

Entrants' problem. At the end of period t, exogenous $M_{i,t}^{PE}$ potential entrants draw idiosyncratic productivity shocks $\{s_i(n)\}_{n\in M_{i,t}^{PE}}$, then, determine the value of entering and starting operations in $t+1$:

$$V_{i,t}(n)^E = \beta \mathbb{E}_\Omega \left[V_{i,t+1}(n)^I | \Omega_t \right] \tag{20}$$

Where $e_{i,t}(n)$ is a random entry cost observed before making the entry decision. Normalizing the outside option to zero, the potential entrant decides to enter in $t+1$ if:

$$V_{i,t}(n)^E - e_{i,t}(n) > 0 \tag{21}$$

The entry shock $e_{i,t}(n)$ explains why certain unproductive firms might enter the market while some highly productive ones might not. As the productivity draw increases, so does the value of entering the market, making it more likely for a firm to choose to enter.

5.4 Local labor productivity

In standard economic-geography models, production in a location takes place in a single representative firm with a production function of the form $Y_{i,t} = A_{i,t}L_{i,t}$, where $A_{i,t}$ is local labor productivity and is exogenously given and, therefore, policy invariant. The key innovation of our framework is that we allow $A_{i,t}$ to depend on local productivity shocks and the endogenous and dynamic firm composition.

Definition 2. *The endogenous* ***location-level labor productivity*** *is:*

$$A_{i,t} \equiv \left[\sum_{n\in M_{i,t}} \varphi_{i,t}(n)^{\sigma-1} \right]^{\frac{1}{\sigma-1}} \tag{22}$$

Notice that definition 2 is isomorphic to a framework in which a location-specific variety is produced using intermediate inputs from local firms and aggregated according to (2). Combining this definition with the firm's production function, the productivity of a location can be rewritten as:

$$A_{i,t} = z_{i,n} \cdot \left[\sum_{n\in M_{i,t}} s_i(n)^{\sigma-1} \right]^{\frac{1}{\sigma-1}} \tag{23}$$

Equation (23) shows that the labor productivity of a location depends on the exogenous productivity shifter $z_{i,t}$, the endogenous number of firms $M_{i,t}$, and importantly, the endogenous idiosyncratic productivity distribution $\{s_i(n)\}_{n\in M_{i,t}}$. The distribution of $s_i(n)$ is determined by the incumbent and potential entrant problems described above and evolves according to the following process:

$$\{s_i(n)\}_{n \in M_{i,t}} = \{s_i(n)\}^I_{n \in M_{i,t-1}} \cup \{s_i(n)\}^E_{n \in M_{i,t}} \tag{24}$$

Intuitively, the current set of producing firms is the union of the sets of surviving firms from the previous period and the potential entrants that decided to start production in t.

Proposition 2. *Output at the location level, given by $Y_{i,t} = A_{i,t}L_{i,t}$, can be decomposed as:*

$$log(Y_{i,t}) = \underbrace{log(z_{i,t})}_{\textit{Technology shock}} + \underbrace{log(\tilde{s}_{i,t})}_{\textit{Firm selection}} + \left(\frac{1}{\sigma - 1}\right) \underbrace{log(M_{i,t})}_{\textit{Varieties}} + \underbrace{log(L_{i,t})}_{\textit{Total labor}} \tag{25}$$

Where $\tilde{s}_{i,t} \equiv \left[\frac{1}{M_{i,t}} \sum_{n \in M_{i,t}} s_i(n)^{\sigma-1}\right]^{\frac{1}{\sigma-1}}$ is the generalized mean idiosyncratic productivity of location i. All terms in the decomposition are positively valued.

Proof. Combine (2), (11), (15) and (16). □

Equation (25) shows that a location will produce more composite output per worker if it faces favorable exogenous technology shocks; if firm selection improves; or if many firms agglomerate in the location.

5.5 Equilibrium

Timing. Figure 5 illustrates the timing of our model. At the beginning of period t, all agents observe the realization of local amenities, productivity shocks, trade costs, and total population. As the composition of firms in period t was decided in $t-1$, local labor productivities, $A_{i,t}$, are immediately determined. Then, households determine labor supply by deciding where to live, taking prices and wages as given.

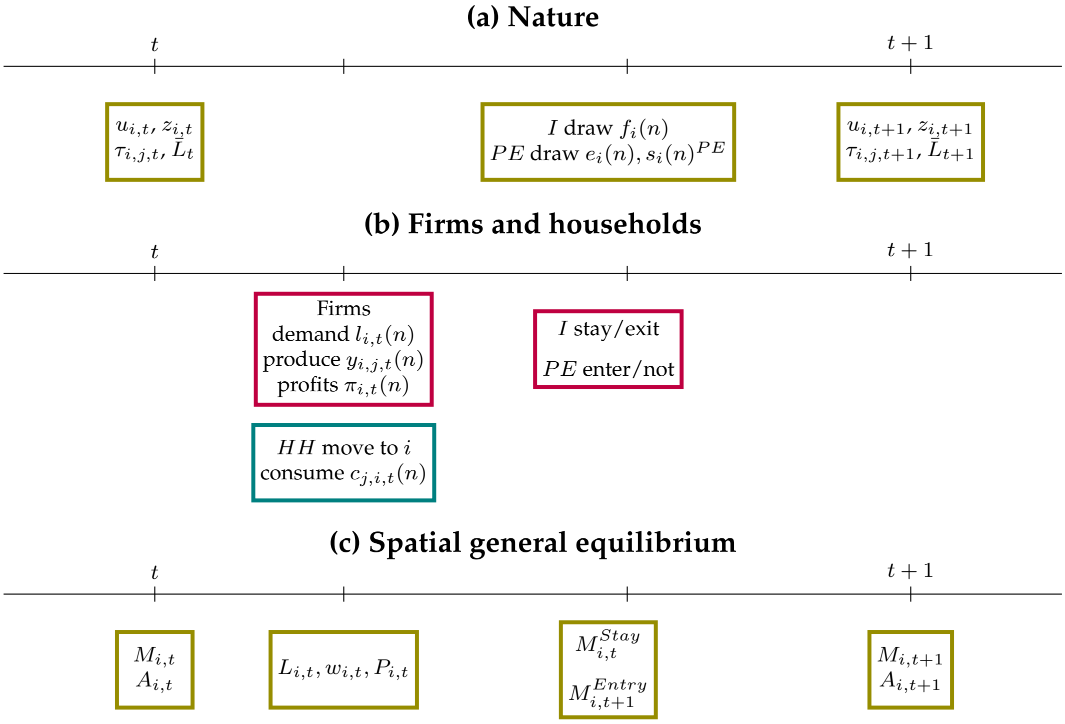
Simultaneously, firms decide their labor demand and production levels, taking market access and wages as given. Finally, profits are realized and redistributed to households. Before the end of the period, incumbent firms decide whether they will continue or exit, and potential entrants decide whether to enter or not. Once these decisions are made, the number and composition of active firms in $t+1$ are determined.

Similar to Caliendo et al. (2019), we establish a distinction between a *temporary* and a *sequential* competitive equilibrium. The *temporary* equilibrium is the solution to the multi-location internal trade model. The *sequential* equilibrium is characterized by the migration decisions of households and the entry and exit decisions of firms.

Definition 3. *Given $\bar{L}_t, u_{i,t}, z_{i,t}, \tau_{i,j,t}$, a **temporary equilibrium** are quantities $L_{i,t}, y_{i,j,t}$ and prices , $w_{i,t}, p_{i,t}(n), P_{i,t}$ such that:*

1. *Households maximize utility given by (4)*
2. *Firms maximize profits given by (13)*

Figure 5: Timing of the model



Notes: I=incumbents. PE=potential entrants. HH=households

3. *Wages $w_{i,t}$ clear local labor markets $\forall i \in \mathcal{J}$:*

$$L_{i,t} = \sum_{n \in M_{i,t}} l_{i,t}(n)$$

4. *Prices $p_{i,j,t}(n)$ clear good markets $\forall n \in M_{i,t}$ and $\forall i, j \in \mathcal{J}$:*

$$c_{i,j,t}(n) = y_{i,j,t}(n)$$

$$w_{i,t} L_{i,t} = \sum_{j \in \mathcal{J}} \sum_{n \in M_j} p_{i,j,t}(n) y_{i,j,t}(n)$$

Definition 4. *Given $\bar{L}_t, u_{i,t}, z_{i,t}, \tau_{i,j,t}$ and $f_{i,t}(n), e_{i,t}(n)$, a **sequential equilibrium** are quantities $L_{i,t}$, $M_{i,t}$ such that:*

1. *Migration decisions solve (10) and utility is equalized across locations $U_{i,t} = U_t \ \forall i \in \mathcal{J}$, moreover:*

$$\sum_{i \in \mathcal{J}} \sum_{j \in \mathcal{J}} (L_{i,t} - L_{j,t-1}) = \bar{L}_t - \bar{L}_{t-1}$$

2. *Entry and exit decisions solve (19) and (21) and:*

$$M_{i,t} = M^S_{i,t} + M^E_{i,t-1} \forall i \in \mathcal{J}$$

Where $M^S_{i,t}$ denotes the mass of surviving firms from $t-1$ to t.

Proposition 3. *The static equilibrium exists, and it is unique; therefore, the sequence of temporary equilibria exists, and is unique. Moreover, for arbitrary constants U_t and ϕ_t, the following system of equations determines the static spatial equilibrium.*

$$L_{i,t}w_{i,t}^{\sigma} = \tilde{\sigma}U_t^{1-\sigma}\sum_{j\in\mathcal{J}}\tau_{i,j}^{1-\sigma}A_{i,t}^{\sigma-1}u_{j,t}^{\sigma-1}L_{j,t}w_{j,t}^{\sigma} \tag{26}$$

$$w_{i,t}^{1-\sigma} = \tilde{\sigma}U_t^{1-\sigma}\sum_{j\in\mathcal{J}}\tau_{i,j}^{1-\sigma}A_{j,t}^{\sigma-1}u_{i,t}^{\sigma-1}w_{j,t}^{1-\sigma} \tag{27}$$

$$L_{i,t}w_{i,t}^{\sigma}A_{i,t}^{1-\sigma} = \phi_t w_{i,t}^{1-\sigma}u_{i,t}^{1-\sigma} = ma_{i,t} \tag{28}$$

Proof. From market clearing, the indirect utility function, and the price index, we obtain (26). From the price index and the indirect utility function we get (27). From theorems 1 and 2 in Allen and Arkolakis (2014) we know that, given $\bar{L}_t, u_{i,t}, A_{i,t}, \tau_{i,j,t}$, the sequence of static equilibrium exists, it is unique, and it satisfies 28. □

Proposition 4. *There is a unique allocation of workers across firms within location given by:*

$$\frac{l_{i,t}(n)}{L_{i,t}} = \left(\frac{s_i(n)}{\bar{s}_{i,t}}\right)^{\sigma-1} \tag{29}$$

Where $\bar{s}_{i,t} \equiv \left(\sum_{n\in M_{i,t}} s_{i,t}(n)^{\sigma-1}\right)^{\frac{1}{\sigma-1}}$.

Proof. Combine equations (16) and (28). □

According to (29), there is a convex relationship between a firm's relative productivity and its relative size. If firms with relatively high levels of productivity enter location i such that firm n is 1% relatively less productive, it will lose $(\sigma-1)$% of its share in the local labor force.

6 Calibration

In this section, we take our model to the Mexican data by using a combination of parameterization, model inversion, and internal calibration. Then, we conduct two validation exercises to test the model's predictive performance.

6.1 Parameterization

Time period and locations. In our model, each period spans five years, aligning with the frequency of our five census waves: 1998, 2003, 2008, 2013, and 2018. We set the 5-year discount rate to $\beta = 0.82$, consistent with an annual discount rate of 0.96. We restrict the number of locations to $\mathcal{J} = 2,463$. The rest have been excluded because they do not consistently appear in all census waves, or they have fewer than 10 firms, which addresses confidentiality concerns. Our 2,463 locations encompass 93% of all firms in 1998 and 85% in 2018.

Elasticity of substitution. We set $\sigma = 9$ for all periods, following Eaton and Kortum (2002) and Allen and Arkolakis (2014). This choice allows us to ensure comparability of our results with standard internal trade models.[18] This value is higher than what is often found in the literature (e.g Hsieh and Klenow (2009)). Lower values of σ would imply lower substitutability across goods and therefore larger gains from the reduction in trade costs.

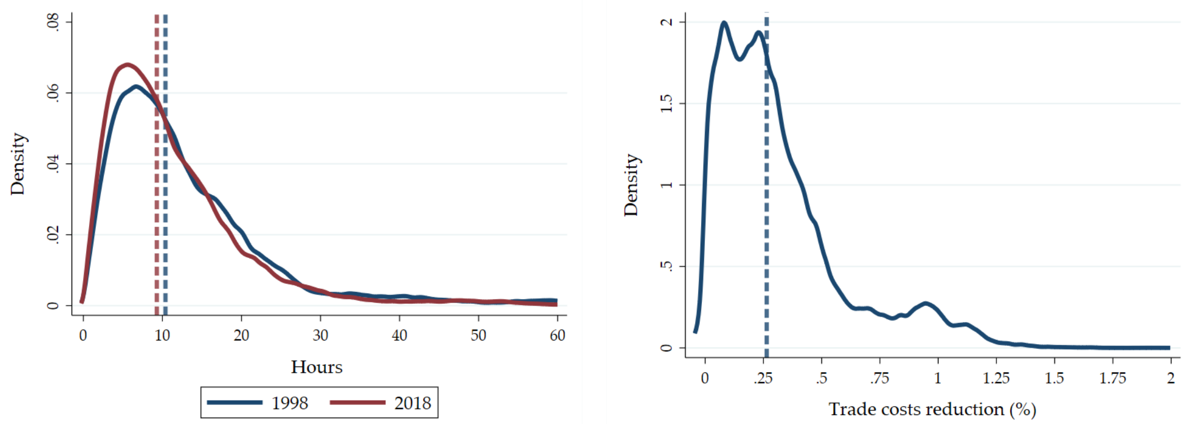
Trade costs. We estimate trade costs $\tau_{i,j,t}$ for all census waves in two-steps. First, we compute the minimum travel time between any two locations, $T_{i,j,t}$, by using the Dijkstra algorithm (Dijkstra, 1959). This algorithm discretizes the space in cells characterized by the speed of their highways. If a cell is not intersected by any highway, we assume a transit speed of 5 km/h. If it is crossed by one or more highways, the transit speed is determined by the one with the highest maximum speed, which ranges from 50 km/h to 120 km/h. We set the speed in cells forming urban agglomerations to be 30 km/h.

Once we have the minimum travel times for all pairs i, j and for all t, we compute the trade costs as in Hanson (2005) and Pérez and Sandoval (2017) assuming the following parametric form:

$$\tau_{i,j} = \begin{cases} e^{\lambda_0 + \lambda_1 T_{i,j}} & \text{if } i \neq j \\ 1 & \text{if } i = j \end{cases} \tag{30}$$

Where λ_0 represents the fixed cost of the goods leaving the location of origin, and λ_1 denotes the additional cost incurred for each additional hour of transportation time. We parameterize this function following Pérez and Sandoval (2017). They estimate $\lambda_0 = 0.0557$ and $\lambda_1 = 0.0024$ for Mexico using price data for avocados, which are a good primarily produced in a single location and sold at prices that increase with travel time. Their estimates imply that when goods leave the location of origin, prices increase immediately by 5.57% and then increase by 5.76% for every 24 hours in transit.

Figure 6: Travel times and reduction in trade costs, 1998-2018



(a) Hours origin-destination

(b) Trade costs reduction, 1998-2018

Notes: Figures show all origin-destination i, j combinations $(3, 234^2)$.

[18] In Gaubert (2018) this is calibrated to match the average revenue-to-cost margin in each sector.

Figure 6 panel (a) shows the distribution of travel time hours for all pairs of origins and destinations in the data. In 1998, the median origin-destination travel time was 13.4 hours. This decreased to 11.6 hours in 2018. Panel (b) shows how the overall reduction in travel times affected the implied trade costs. The median origin destination pair (i, j) saw a reduction of 0.26% in trade costs.

6.2 Labor and wage paths

Labor and wages. We assume that the observed geographical distributions of wages $w_{i,t}$ and labor $L_{i,t}$ across locations are equilibrium outcomes of the model. We measure the local labor distribution $\{L_{i,t}\}_{i\in\mathcal{J}}$ as the number of workers reported in the census.

The distribution of local wages $\{w_{i,t}\}_{i\in\mathcal{J}}$, is obtained by residualizing wages in two steps. First, we compute local average wages $\bar{w}_{i,t}$ as total wage bill over the number of workers. And second, we regress it on local observable characteristics that are not accounted for by our model and use the estimated residuals as local wages. The regression model is:

$$\bar{w}_{i,t} = \beta_0 + \beta_1\%\ \text{educ}_{i,t} + \beta_2\%\ \text{manuf}_{i,t} + \beta_3\text{K/L}_{i,t} + \beta_4\%\ \text{inf}_{i,t} + \epsilon_{i,t} \tag{31}$$

Where i denotes the location and t the census year. The regression accounts for heterogeneity in education, industrial composition, capital intensity, and informality. Figure 18 in Appendix C shows the correlation between residualized wages and local population. Wages in large locations are higher even after controlling by observable characteristics. This is in line with a story in which locations with highly productive firms increase both local labor productivity and wages, and thus attract more workers.

6.3 Model inversion

Local amenities and productivity. We invert the model to retrieve the distribution of local amenities $u_{i,t}$ and local labor productivity $A_{i,t}$. For a given geography of trade costs, differences in amenities are identified from differences in population in locations with similar wages. On the other hand, differences in labor productivity are identified from differences in labor income in locations with similar amenities. Formally, (32) and (33) retrieve amenities and productivities from an observed distribution of trade costs, local labor, and wages.[19]

$$u_{i,t}^{1-\sigma} = \frac{\tilde{\sigma}U_t^{1-\sigma}}{\phi_t}\sum_{j\in\mathcal{J}} \tau_{i,j,t}^{1-\sigma} w_{i,t}^{\sigma-1} w_{j,t}^{\sigma} L_{j,t} u_{j,t}^{\sigma-1} \qquad \forall i \in \mathcal{J} \tag{32}$$

$$A_{i,t} = \left[\frac{1}{\phi_t} L_{i,t} w_{i,t}^{2\sigma-1} u_{i,t}^{\sigma-1}\right]^{\frac{1}{\sigma-1}} \qquad \forall i \in \mathcal{J} \tag{33}$$

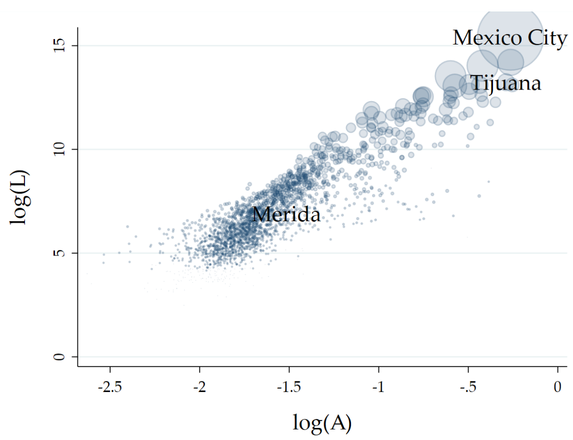
To determine ϕ_t we use the equilibrium in the labor market $\bar{L}_t = \sum_{i\in\mathcal{J}} L_{i,t}$:

[19]Endogenous constants U_t and ϕ_t are not identified in levels. We normalize them to one at baseline.

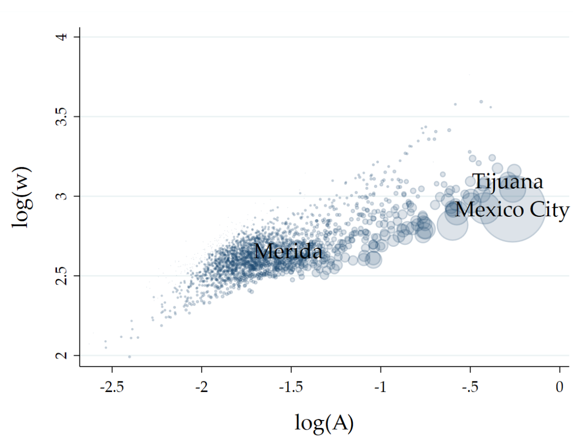
$$\phi_t = \bar{L}_t \left(\sum_{i \in \mathcal{J}} w_{i,t}^{1-2\sigma} u_{i,t}^{1-\sigma} A_{i,t}^{\sigma-1} \right)^{-1} \tag{34}$$

Figure 7 illustrates the correlation between amenities, labor productivity, population, and wages. Two contrasting cases, Tijuana and Merida, highlight how these variables interact. Tijuana is a dangerous city located in the northern Mexican desert, while Merida, situated near the Caribbean Sea, is renowned for its safety. Tijuana has limited local amenities in comparison to Merida; nonetheless, Tijuana has higher population and wage levels than Merida. This is explained by Tijuana's higher local labor productivity, which is driven by its highly productive firms in the export-oriented manufacturing sector.

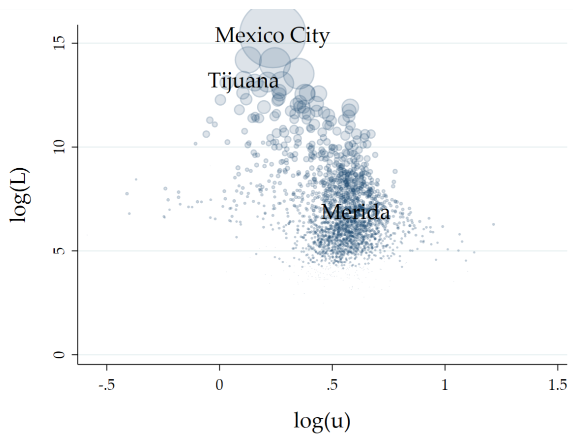
Figure 7: Amenities, productivity, and equilibrium outcomes, 2018



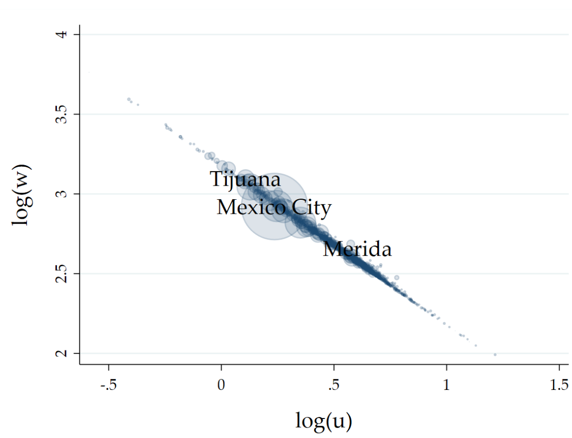
(a) Productivity and employment



(b) Productivity and wages



(c) Amenities and employment



(d) Amenities and wages

Notes: Marker size denotes the number of firms in the location.

6.4 Internal calibration

Once we have fully characterized the path of aggregate location-level equilibrium outcomes, we exploit the microdata to determine the primitives that govern firm dynamics in the model. These are the path of location-level productivity shocks, the initial distribution of idiosyncratic productivities, the entry- and exit-cost distributions, and the path of potential entrants.

Location-specific productivity shock. From (23) and defining

$$\bar{s}_{i,t} \equiv \left[\sum_{n \in M_{i,t}} s_i(n)^{\sigma-1} \right]^{\frac{1}{\sigma-1}}, \tag{35}$$

we solve for the location-specific productivity shock as follows:

$$z_{i,t} = \frac{A_{i,t}}{\bar{s}_{i,t}} \tag{36}$$

Computation of $z_{i,t}$ requires first $A_{i,t}$ which comes from model inversion described above; and second, the distribution of firm-level idiosyncratic productivity, which is a sequential equilibrium outcome. This distribution $\{s_{i,t}(n)\}_{n \in M_{i,t}}$ $\forall i \in \mathcal{J}$ depends on the initial distribution of idiosyncratic productivities and the entry and exit costs' stochastic distributions.

Initial idiosyncratic productivity distribution. To identify the initial distribution of $s_{i,t}(n)$ we assume that the economy reached the steady state in 1998 starting from an arbitrary point in the past. Then, we exploit the result that in equilibrium:

$$\frac{l_{i,t}(n)}{L_{i,t}} = \left(\frac{s_{i,t}(n)}{\bar{s}_{i,t}} \right)^{\sigma-1} \tag{37}$$

Thus, the observed distribution of firm-level labor demand is fully informative about the initial idiosyncratic productivity distribution. More precisely, if $\tilde{l}_{i,t}(n) = \left(\frac{1}{\sigma-1}\right) [log(l_{i,t}(n)) - log(L_{i,t})]$ follows an arbitrary distribution $F(\mu_{\tilde{l}}, \sigma_{\tilde{l}})$, then, $s_{i,t}(n)$ follows $F(\mu_{\tilde{l}} + log(\bar{s}_{i,t}), \sigma_{\tilde{l}})$. From firm-level data we compute $\mu_{\tilde{l}}, \sigma_{\tilde{l}}$, and then we solve the fixed-point problem until $\bar{s}_{i,t}$ is consistent with the equilibrium condition.[20]

Potential entrants' productivity distribution. The distribution of idiosyncratic productivities is governed by $F(\mu_s, \sigma_s)$. Assuming that we know $F(\mu_f, \sigma_f)$ and $F(\mu_e, \sigma_e)$, we estimate the parameters μ_s, σ_s by solving the following problem:[21]

$$\{\hat{\mu}_s, \hat{\sigma}_s\} = arg \min_{\mu_s, \sigma_s} \sum_{i \in \mathcal{J}} \sum_{n \in M_i} \cdot \left[log(l_i(n)^{data}) - log(l_i(n)^{model}) \right]^2 \tag{38}$$

Here, $l_i(n)$ is the number of workers in a firm in the data, and $l_i(n)^{model}$ is the labor demand in the model according to Equation 16. Intuitively, conditional on a set of values for the entry and exit costs, the optimal estimators of μ_s, σ_s are the ones that minimize the square percentage deviations in labor demands observed in the data and the ones implied in the model.

Exit costs. We estimate the exit-cost parameters as follows: first, recall that a firm at

[20] In the quantitative section we assume $F(.)$ is log normal and that $\mu_{\tilde{l}}, \sigma_{\tilde{l}}$ are location specific.
[21] We need to add more details on the definition and existence of a steady state.

the end of period t stays in the market for period $t+1$ if the expected continuation value in $t+1$ minus a cost shock observed at the end of t is higher than the outside option, which we normalize to zero. Denote the continuation value as:

$$x_{i,t}(n) = \beta \mathbb{E}_{\Omega}\left[V_{i,t+1}(n)|\Omega_t\right] \tag{39}$$

Suppose that the cost shock, denoted as $f_{i,t}(n)$, comes from a Gumbel probability distribution $G(.)$. The survival probability of a firm is then:

$$\lambda(x_{i,t}(n)) = \mathbb{P}[x_{i,t}(n) > f_{i,t}(n)] = G(x_{i,t}(n)) \tag{40}$$

Denoting the location parameter μ_f and the spread parameter σ_f, we obtain:

$$\lambda(x_{i,t}(n)) = e^{-e^{-\left(\frac{x_{i,t}(n)-\mu_f}{\sigma_f}\right)}} \tag{41}$$

To compute $x_{i,t}(n)$ we assume that firms form myopic expectations denoted as $\tilde{\mathbb{E}}$ about the future-state space Ω_{t+1}. This implies that $\tilde{\mathbb{E}}_{\Omega}\left[V_{i,t+1}(n)|\Omega_t\right] = V_{i,t}(n)$. Then, the survival probability is the solution to the non-linear system given by equations 17 and 41, which gives:

$$\lambda(w_{i,t}l_{i,t}(n)) = \frac{1}{\beta} - \frac{\frac{1}{\sigma-1}w_{i,t}l_{i,t}(n)}{\mu_s - \sigma_s log[-log[\lambda(w_{i,t}l_{i,t}(n))]]} \tag{42}$$

Equation 42 shows that there is a non-linear mapping between the firm-level equilibrium wage bill $w_{i,t}l_{i,t}(n)$ and the survival probability $\lambda(w_{i,t}l_{i,t}(n))$. We leverage this relationship to retrieve the cost-shock-distribution parameters μ_f, σ_f by solving for the parameters of the cost-shock distribution that will solve the minimization problem:

$$\{\hat{\mu}_f, \hat{\sigma}_f\} = arg \min_{\mu_f,\sigma_f} \sum_{i\in\mathcal{J}} \sum_{n\in M_i} \cdot \left[\lambda(w_{i,t}l_{i,t}(n))^{data} - \lambda(w_{i,t}l_{i,t}(n))^{model}\right]^2 \tag{43}$$

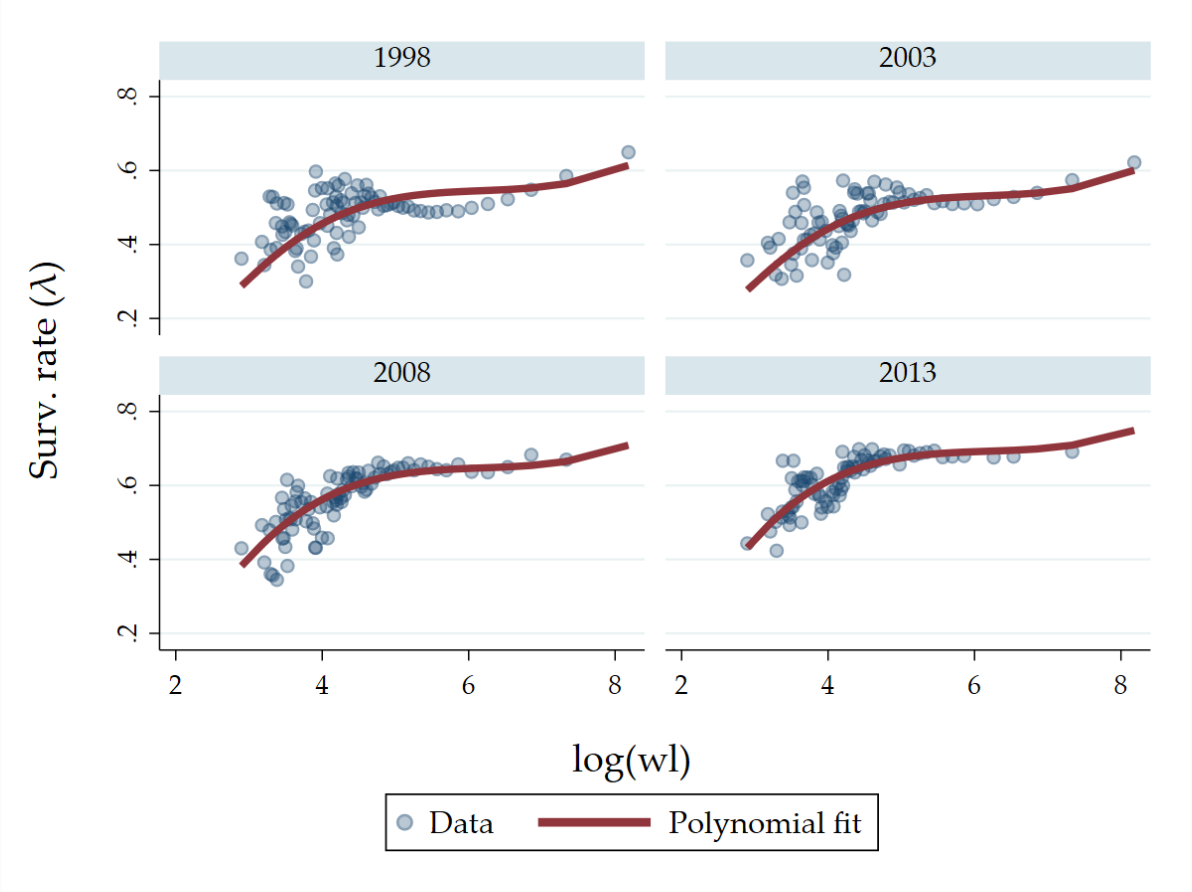
Problem (43) requires that the full mapping between wage bill and exit rates are defined in the data. Since the data are granular, we approximate this relationship by grouping all wage-bill values in percentiles and then computing the associated exit rate. Finally, we approximate this relationship with a polynomial fit, using this continuous approximation as the values targeted by the minimization problem.

Figure 8 shows the polynomial fit ant the survival rates in the data. Notice that survival rates are concave for the low and middle sections of the wage-bill distribution and convex for the high end. This implies that when very large firms shrink, their survival rates decrease faster than when small firms in terms of wage bill do.

Potential entrants and entry costs. At every period we observe in the data the productivity distribution of entrants and their number. However, since by definition we do not observe the potential entrants, there are infinitely many combinations of potential entrant distributions and entry costs that rationalize the observed entrants in the data.

To address this problem we assume first that entry costs $e_i(n)$ are drawn from the same

Figure 8: Wage bill (wl) and survival rate λ in the data



Notes: Each dot is a percentile p in the wage-bill distribution. The polynomial fit of degree d estimated with the ordinary- least-squares (OLS) model: $log\left(\frac{\lambda_{p,t}}{1-\lambda_{p,t}}\right) = \sum_d \gamma_d log(wL_{p,t})^d + \gamma_t + \varepsilon_{p,t}$. For $d = 3$, $\gamma_1 = 3.206, \gamma_2 = -0.512, \gamma_3 = 0.028$.

distribution as exit costs $f_i(n)$. Then, for a given productivity distribution of potential entrants, we back up the mass of potential entrants $\{M_{i,t}^{PE}\}_{i\in\mathcal{J}}$ by solving their entry problem until the implied number of entrants $\{M_{i,t}^{E}\}_{i\in\mathcal{J}}$ plus the survivors $\{M_{i,t}^{S}\}_{i\in\mathcal{J}}$ is equal to the number of firms observed in the next period $\{M_{i,t+1}\}_{i\in\mathcal{J}}$.

Finally, to recover the parameters governing the productivity distribution of potential entrants we assume that they follow a process $F(\mu_E, \sigma_E)$. Then we solve their entry problem, combine these entrants with the survivors, and verify if this productivity distribution is consistent with the one observed in the next period. We iterate on μ_E, σ_E until we reach convergence.

6.5 Model validation

Local productivity. Local labor productivity $A_{i,t}$ is identified without production data. As a validation exercise, we show that its correlation with its data counterpart, based on firm-level output data, is strong. We do this by computing $\hat{A}_{i,t}$ as in (22), with $\hat{\varphi}_{i,t}(n)$ estimated as value added per worker.

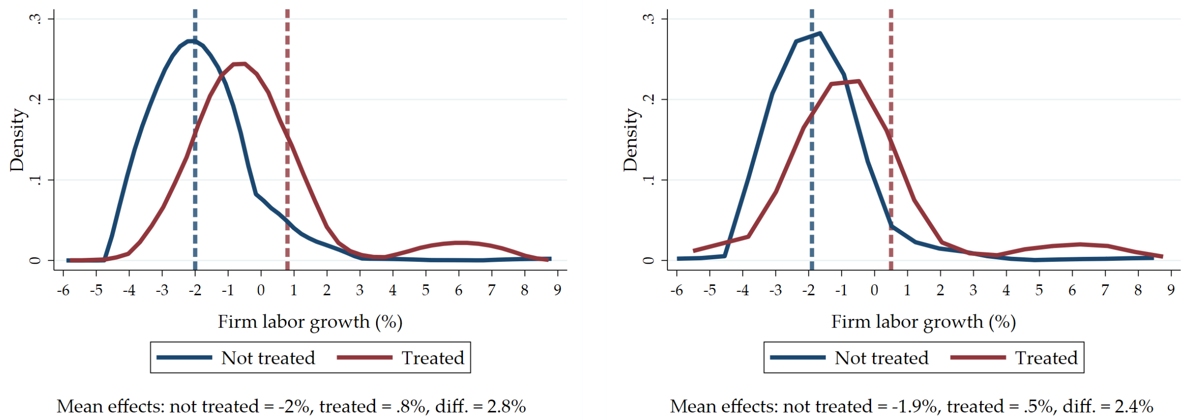
Figure 19 in the appendix shows that, for all years, the R^2 of regressing model-implied and empirical local labor productivity is close to 0.8. This suggests that the model-implied local labor productivity captures most of the variation in the data. The remaining 0.2 of the variation comes from mechanisms absent in out model, such as industrial heterogeneity or spatial frictions in human capital mobility.

Natural experiment replication. We further validate the model by replicating the natural experiment from Section 4 inside the model and showing that it provides similar point estimates. We do this by creating a counterfactual scenario in which we effectively shut down all new highways, eliminating all plans that were constructed from 2013 to 2018. We then compare outcomes from the data and from this counterfactual exercise for both treated and untreated groups.[22]

Table 6 column (3) shows that the empirical point estimate is 1.6% in a 90% confidence interval of [0.1%, 3.1%]. Figure 9 panel (a) shows that the associated effect in the model is 2.8%, which falls within the confidence interval. We interpret this as reasonable evidence that the model is capable of capturing the observed behavior in the data.

Furthermore, we use the model to argue that the *"no anticipation of the treatment"* assumption in the empirical exercise implies an underestimation of our estimates. To address this issue, we allow firms in 2013 to expect that all announced construction plans will be built and to make their surviving decisions accordingly. We then compare treated and untreated groups in 2018. Panel (b) reveals that if we allow firms to react to the announcement, the net effect is 0.4 percentage points smaller, which is still within the confidence interval but closer to the empirical estimate. This result suggests that our empirical estimates are likely to be a lower bound of the true effect.

Figure 9: Effects of new highways 2013-2018 model vs natural experiment



(a) Firms do not expect plans to be executed (b) Firms expect plans to be fullyl executed

Notes: The figure shows the replication of natural experiment for 2013-2018 construction plans. In panel (a) incumbent firms do not expect plans to be executed. In panel (b) incumbent firms expect all plans to be executed. Vertical dashed lines denote the corresponding average effect.

[22] We do not limit the exercise to eliminating only highways from the construction plans; this is because our empirical estimates may also capture effects from secondary roads or other highways that influence both the treatment and control groups.

7 Quantitative results

7.1 Contribution of highways to welfare and growth

Between 1998 and 2018, the network of paved roads and highways in Mexico expanded from approximately 100,000 kilometers to nearly 200,000 kilometers. In this section, we show that this expansion produced modest welfare and income gains but high reallocation of economic activity across locations. We then show that firm dynamics were a key driver of both the aggregate and distributional effects. To analyze these dynamics we construct a counterfactual scenario in which the trade geography remains at 1998 levels, and we then recalculate the growth trajectory using our model. We interpret the difference between this counterfactual scenario and the path in the data as the contribution of highways that were constructed between 1998 and 2018.

Welfare and aggregate effects. New highways built from 1998 to 2018 increased welfare, real income, and productivity. Table 7 shows the comparisons of results from the counterfactual scenario in which the highway network remained as it was in 1998 and those outcomes as shown in our data that actually occurred in 2018. Welfare is 0.44% higher. Real income is 0.64% higher. And aggregate productivity is 0.13% higher. The number of firms, however, is 0.10% lower.

Welfare gains are entirely explained by the increase in real income as amenities are exogenous. The findings of Allen and Arkolakis (2014) serve as a reference for the extent of welfare gains; they document that the entire interstate highways network in the US increased welfare by 1.3%. As our model reveals, real income rises for two reasons. First, labor productivity improves, leading to higher nominal wages. Second, reductions in trade costs drive down prices of goods, as indicated by reductions in local price indices. The increase in productivity is explained by positive firm selection, driven by higher survival and entry rates of productive firms. Then, too, a more efficient transportation system requires fewer firms in the aggregate, as lower trade costs allow fewer firms to serve more markets.

Table 7: Gains from highways

Year	(1) Welfare	(2) Real income	(3) Productivity	(4) Firms
1998	0.00%	0.00%	0.00%	0.00%
2003	0.13%	0.09%	0.04%	-0.04%
2008	0.24%	0.36%	0.25%	-0.02%
2013	0.40%	0.40%	0.22%	-0.07%
2018	0.44%	0.64%	0.13%	-0.10%

Notes: Gains measure how much higher outcomes are with respect to a counterfactual in which none of the new highways after 1998 were built. L denotes total labor productivity as in (22). wL/P is total real remunerations. M is the total number of firms.

Distributional effects. Aggregate results hide important distributional effects across space. To illustrate this point, Table 8 shows gains at the 25th, 50th and 75th percentile levels in labor, real income, labor productivity, and number of firms that result from new infrastructure across all locations from 1998 to 2018.

People migrate until utility is equalized; thus, there is no dispersion in welfare gains. This leads to net migration-implied population gains of at least 5% above the 75th percentile and similar levels of losses below the 25th percentile. Due to these population losses, as shown by Column (2), real income fell in more than half of the locations, while, at the same time, real income for those whose earnings were in the top 75th percentile rose by at least 5%.

Firms react differently across space to new transport infrastructure. As shown in Column (3), labor productivity decreased in half of the locations due to exit of productive firms. Even though, in the aggregate, better transport infrastructure implies that fewer firms are needed, this is mostly driven by net exits of firms in locations locations that are farther away from the highway network. As Column (4) shows, there was a net decrease in the number of firms in more than half of locations, but a net increase of at least 2.34% in a quarter of locations.

Table 8: Distribution of impacts from new highways

Percentile	(1) Labor	(2) Real income	(3) Productivity	(4) Firms
25th	-5.76%	-5.32%	-0.60%	-2.65%
50th	-0.94%	-0.50%	0.01%	-0.12%
75th	5.17%	5.60%	0.58%	2.34%

Notes: The table shows the impacts on labor, real income, productivity and the number of firms from the new highway network by comparing outcomes with those that would have emerged in a counterfactual scenario in which the highway network had remained unchnaged since 1998. L denotes total labor productivity as in (22). wL/P is total real income. M is the total number of firms.

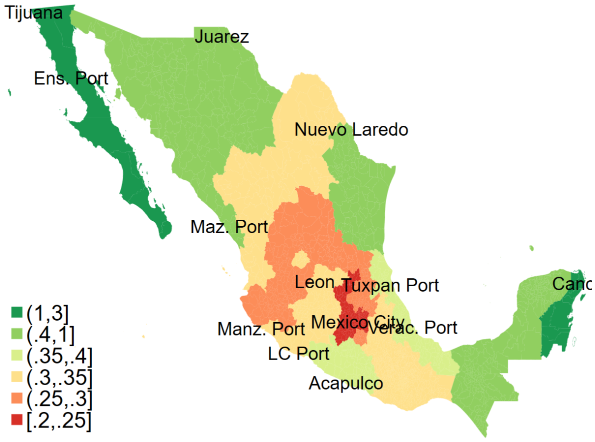
To understand the geographical concentration of these heterogeneous gains, we show in Figure 10 the state-average impacts on key economic outcomes.[23] In general, the states that experienced the largest gains are those situated near to the main port of entry to California (Tijuana) or to the Caribbean Sea, the largest tourist hub (Cancun). The states that saw moderate gains are those located near the port of entry to New Mexico and Texas (Juarez and Nuevo Laredo) or to the main sea ports connecting Mexico to Asia (Manzanillo) and Europe (Veracruz). The remaining states mostly incurred losses, indicating that more economic activity would have been concentrated there in the absence of the new transport infrastructure.

Panel (a) in Figure 10 shows that consumers in better connected areas can purchase goods at prices that are as much as 3% lower. According to panel (b), demand for goods produced also increases by up to 5% these locations. Panels (c) and (d) further reveal that these effects result in positive net population growth ranging from 10% to 40%, along with similar real revenue gains. In panel (e), it is shown that in these locations, the introduction of new highways increases the number of firms by 1% to 5%. While these firms may vary in productivity levels, the addition of the new highways is predominantly productivity enhancing (see panel (f)). The opposite holds true for areas with limited exposure to new transport infrastructure; these firms largely experience .

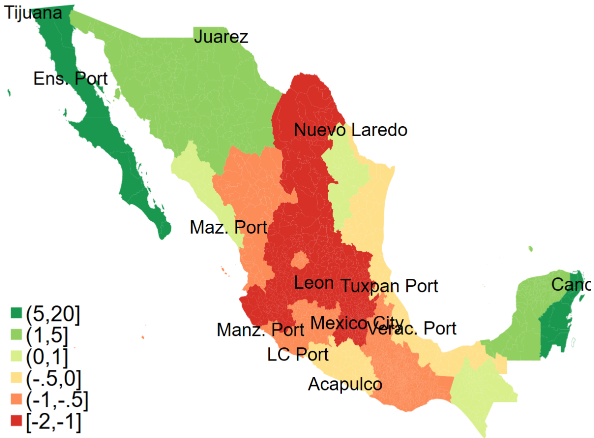
Contribution of firm dynamics. We quantify the role played by firm dynamics in the aggregate and distributional effects of new transport infrastructure in two ways. First, we compare the effects of highways on economic outcomes in our model to the effects

[23]We calculate these averages weighted by population. State-level averages are used for clarity in presentation. Figure 20 in the Appendix shows maps with impacts at the location level.

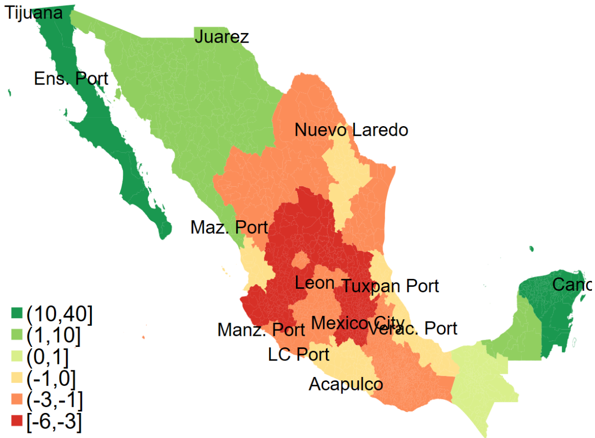
Figure 10: Average impacts from the highway network expansion (1998-2018)



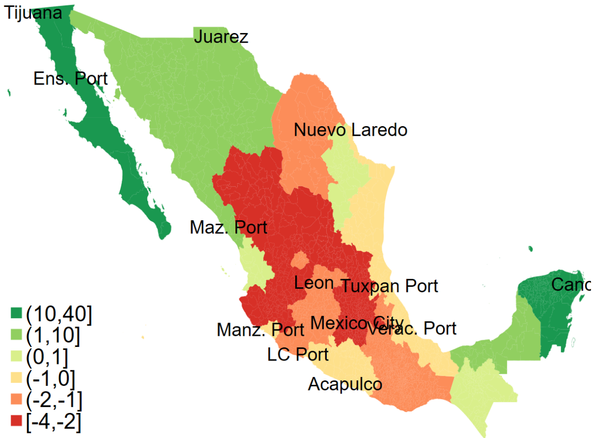
(a) Impacts on the price index (%)



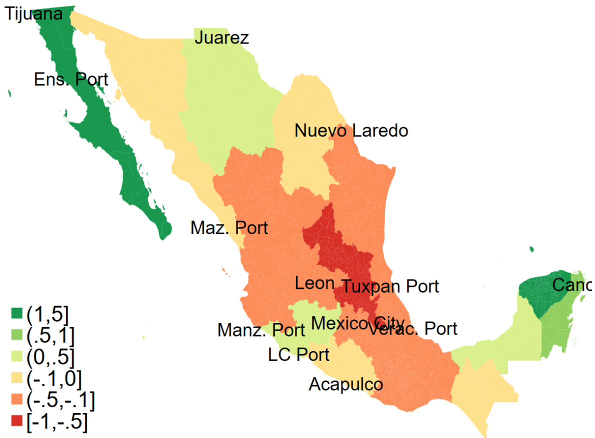
(b) Impacts on market access (%)



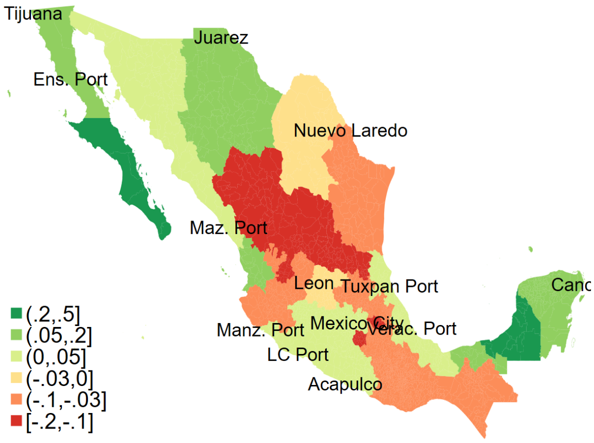
(c) Impacts on employment (%)



(d) Impacts on real revenue (%)



(e) Impacts on the number of firms (%)



(f) Impacts on productivity (%)

Notes: The maps show the impacts that stem from expanding the highways network over the period from 1998 to 2018. Changes are shown at the state level and are calculated by averaging locations weighted by population. Impacts at the municipal level are shown in Figure 20 in Appendix C.

predicted by standard trade models, which assume a static economy and exogenous local productivity. Notice that our model collapses to this framework by assuming an infinitely lived, single representative firm by location (Allen and Arkolakis, 2014).

Table 9 shows welfare and income gains when we abstract from firm dynamics. We omit gains in productivity and the number of firms because they are zero by definition in the absence of dynamic firm behavior. Column (1) shows that welfare gains in the absence of firm dynamics are slightly smaller. In terms of the impacts on welfare, this result suggests that the reduction in trade costs, not local productivity, matters the most for individuals. A key driver of this result is the assumption of free mobility. In terms of real income, firm dynamics play a bigger role. When we allow for firm dynamics, income gains in 2003 are 0.09%, while a standard model would imply gains of 0.05%. This means that 55% of the real revenue gains come from the reduction in trade costs induced by better highways, and that the remaining 45% of real income gains come from local productivity gains driven by firm dynamics. The contribution of firm dynamics is 11% for 2008, 16% for 2013 and 7.6% for 2018.

Table 9: Gains from highways, without including firm dynamics

Year	(1) Welfare	(2) Real income
1998	0.00%	0.00%
2003	0.11%	0.05%
2008	0.24%	0.32%
2013	0.39%	0.34%
2018	0.44%	0.59%

Notes: The table shows how much welfare and real income increased following the building of highways over the 1998-2018 period with respect to a counterfactual scenario that would have emerged had no new highways been built. The productivity and number of firms in a given location are kept fixed.

A model overlooking firm dynamics not only underestimates gains from the construction of new highways but also their dispersion. Table 10 shows that the interquartile range of labor gains is 9.98%, compared to 10.93% in our baseline model. Similarly, for real income gains. This result suggests that firm dynamics are a force for spatial divergence when new transport infrastructure is unequally targeted across space.

Table 10: Distribution of gains from highways, without including firm dynamics

Percentile	(1) Labor	(2) Real income
25th	-5.32%	-4.87%
50th	-0.72%	-0.27%
75th	4.67%	5.12%

Notes: The table shows how much welfare and real income increased following the building of highways over the 1998-2018 period with respect to a counterfactual scenario that would have emerged had no new highways been built. The productivity and number of firms in a given location are kept fixed.

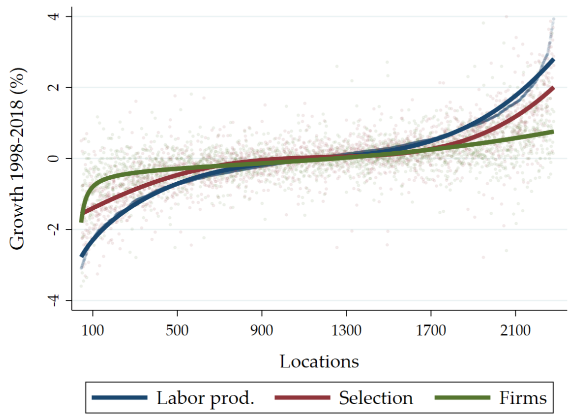
Second, we compute the extent to which the increase in local labor productivity induced by transport infrastructure can be attributed to firm selection or net firm entry.

Notice that in a model without firm dynamics both are zero. Equation (25) implies that:

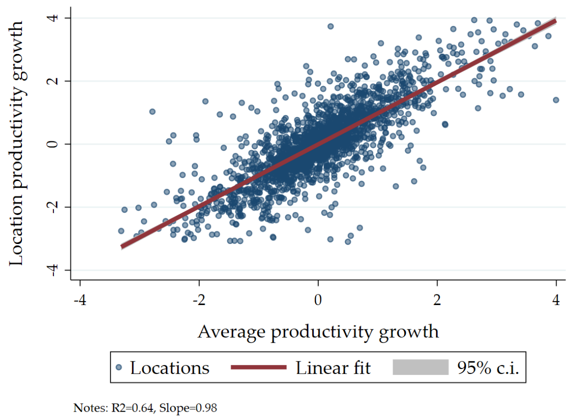
$$\Delta log(A_{i,t})^{baseline} - \Delta log(A_{i,t})^{no\ new\ highways} = \Delta log(\tilde{s}_{i,t})^{baseline} - \Delta log(\tilde{s}_{i,t})^{no\ new\ highways} + \Delta log(M_{i,t})^{baseline} - \Delta log(M_{i,t})^{no\ new\ highways} \quad (44)$$

Equation (44) captures the fact that some firm selection and net firm entry would have taken place in a counterfactual with no new highways over the period from 1998 to 2018. The difference between this counterfactual and what we observe in the data captures the responses of firms to new infrastructure.

Figure 11: Decomposition of local productivity growth induced by new highways (1998-2018



(a) Decomposition of productivity growth



(b) Correlation between location productivity and firm selection

Notes: Productivity is measured by $A_{i,t}$. Selection is measured by average idiosyncratic productivity $\tilde{s}_{i,t}$. Firms are measured by $M_{i,t}$. Dots show the J locations, and lines show a polynomial fit of degree 3.

Figure 11 shows the decomposition in (44) for all locations. Panel (a) shows that, in half the locations, new transportation infrastructure decreased labor productivity. Moreover, for most of the locations a larger portion of the total change is explained by firm selection rather that by net firm entry. In panel (b), we regress labor productivity growth on firm-selection growth induced by new highways over the period from 1998 to 2018. According to the R^2, 64% of the variation in labor productivity growth is explained by variation in firm selection.

7.2 A more ambitious infrastructure policy

Between 1998 and 2018 the paved roads network in Mexico doubled. The median origin-to-destination travel time (to drive from municipalities in Mexico to Mexico City) fell by 13% in 20 years, from 13.4 to 11.6 hours. Mexico has 1.4 meters of paved roads per capita. This is one-tenth of the equivalent figure for the US, Mexico's neighbor and largest trading partner. The disparity raises the question: What would have happened if infrastructure investments had been more ambitious over the period we study?

We use our calibrated model to answer this question by focusing on an alternative infrastructure policy in which the percentage reduction in travel times is twice as great as the levels calculated by using the 1998-2018 data; we then compare the likely outcomes from the two counterfactual scenarios: 1) the scenario in which the speed made possible from the highway network is twice that of the speed possible from the network that was constructed by 2018, and 2) the scenario that would have likely occurred in 2018 had no new highways been built after 1998.

Table 11: Likely impacts of a highway network twice as fast as the 2018 network

Year	(1) **Welfare**	(2) **Total wL/P**	(3) **Total A**	(4) **Total M**
1998	0.00%	0.00%	0.00%	0.00%
2003	0.21%	0.10%	0.01%	-0.08%
2008	0.45%	0.49%	0.28%	-0.05%
2013	0.59%	0.56%	0.24%	-0.12%
2018	0.84%	1.10%	0.14%	-0.12%

Notes: The table compares the impacts from two counterfactual scenarios, one in which journeys are twice as fast as those made possible by the network that existed in 2018, and one in which the highway network in 2018 remained the same as it had been in 1998.

Table 11 shows the results of this experiment. Column (1) shows that welfare and real revenue gains in 2018 would have been nearly double the level of gains from the actually built highways. Although labor productivity would be higher with a speedier highway network than the one that was constructed, the difference is small.

Table 12: Distribution of impacts if the highways were twice as fast as the 2018 network

Percentile	(1) **Labor**	(2) **Real income**	(3) **Productivity**	(4) **Firms**
25th	-5.14%	-5.55%	-0.62%	-2.64%
50th	0.60%	0.19%	-0.02%	0.00%
75th	5.62%	5.21%	0.59%	2.47%

Notes: The table compares impacts from two counterfactual scenarios: one in which the highway network is twice as fast as the 2018 network that was constructed, and one in which no new highways were built after 1998. L denotes total labor productivity as in (22). wL/P denotes total real income. M denotes the total number of firms.

Finally, Table 12 shows that, although the welfare and real income gains are larger, the unequal distribution of these benefits is preserved. This exercise highlights that proportionally improving the highways network has aggregate benefits but no effects on regional convergence.

8 Conclusion

This paper reveals that firm dynamics are a key determinant of the aggregate and distributional effects of new transportation infrastructure. We empirically document that new transportation infrastructure increases labor productivity, firms' total factor productivity, and entry and exit rates of firms.

We introduce a novel, spatial general-equilibrium model with heterogeneous firm dynamics to show that infrastructure policies affect aggregate income an welfare in two ways. The first is a direct effect: better transportation infrastructure reduces trade costs for goods, which is transmitted to consumers in the form of lower prices, and to firms as higher demand. This second is an indirect effect: new transport infrastructure increases entry and survival of productive firms in locations that are better integrated into the transportation network; this translates into higher labor productivity, income, and welfare.

These effects, however, are unequally distributed across space and among income levels. Regions close to the US border, to sea ports, and to tourist hubs are better exposed to new transportation infrastructure so they disproportionally benefit the most. Besides having greater market access, these regions also attract and keep productive firms. The opposite is true for less expose locations, mostly concentrated in the center of the country.

All in all, transport infrastructure is likely to have stronger distributional than aggregate effects, especially in situations in which the highways network is underdeveloped, as is the case in Mexico. An interesting avenue for future research could examine whether a place-based system of taxes and transfers can help mitigate the negative effects of low infrastructure investments in remote locations.

References

Ackerberg, D. A., Caves, K., and Frazer, G. (2015). Identification properties of recent production function estimators. *Econometrica*, 83(6):2411–2451.

Ahlfeldt, G. M. and Feddersen, A. (2018). From periphery to core: measuring agglomeration effects using high-speed rail. *Journal of Economic Geography*, 18(2):355–390.

Allen, T. and Arkolakis, C. (2014). Trade and the topography of the spatial economy. *The Quarterly Journal of Economics*, 129(3):1085–1140.

Allen, T. and Arkolakis, C. (2022). The welfare effects of transportation infrastructure improvements. *The Review of Economic Studies*, 89(6):2911–2957.

Arkolakis, C., Costinot, A., Donaldson, D., and Rodríguez-Clare, A. (2019). The elusive pro-competitive effects of trade. *The Review of Economic Studies*, 86(1):46–80.

Asturias, J., García-Santana, M., and Ramos, R. (2019). Competition and the welfare gains from transportation infrastructure: Evidence from the golden quadrilateral of india. *Journal of the European Economic Association*, 17(6):1881–1940.

Audretsch, D. B., Dohse, D., and dos Santos, J. P. (2017). Do toll-free highways foster firm formation and employment growth? results from a quasi-natural experiment. Technical report, Kiel Working Paper.

Azkarate-Askasua, M. and Zerecero, M. (2022). The aggregate effects of labor market concentration. *Available at SSRN 4323492*.

Baker, A. C., Larcker, D. F., and Wang, C. C. (2022). How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics*, 144(2):370–395.

Banerjee, A., Duflo, E., and Qian, N. (2020). On the road: Access to transportation infrastructure and economic growth in china. *Journal of Development Economics*, 145:102442.

Blankespoor, B., Bougna, T., Garduno Rivera, R., and Selod, H. (2017). Roads and the geography of economic activities in mexico. *World Bank Policy Research Working Paper*, (8226).

Borusyak, K. and Hull, P. (2020). Non-random exposure to exogenous shocks: Theory and applications. Technical report, National Bureau of Economic Research.

Busso, M., Fazio, M., and Algazi, S. (2012). (in) formal and (un) productive: The productivity costs of excessive informality in mexico.

Busso, M., Fentanes, O., and Levy Algazi, S. (2018). The longitudinal linkage of mexico's economic census 1999-2014. *Manuscript, Inter-American Development Bank, Washington, DC*.

Caliendo, L., Dvorkin, M., and Parro, F. (2019). Trade and labor market dynamics: General equilibrium analysis of the china trade shock. *Econometrica*, 87(3):741–835.

Callaway, B. and Sant'Anna, P. H. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2):200–230.

Chaney, T. (2008). Distorted gravity: the intensive and extensive margins of international trade. *American Economic Review*, 98(4):1707–1721.

Chang, Z. and Zheng, L. (2022). High-speed rail and the spatial pattern of new firm births: Evidence from china. *Transportation Research Part A: Policy and Practice*, 155:373–386.

Combes, P.-P., Duranton, G., Gobillon, L., Puga, D., and Roux, S. (2012). The productivity advantages of large cities: Distinguishing agglomeration from firm selection. *Econometrica*, 80(6):2543–2594.

Dávila, E., Kessel, G., and Levy, S. (2002). El sur también existe: un ensayo sobre el desarrollo regional de méxico. *Economía Mexicana Nueva Época, volumen XI, número 2, 2do semestre de 2002, pp 205-260*.

Dijkstra, E. (1959). A note on two problems in connexion with graphs. *Numerische mathematik*, 1(1):269–271.

Dixit, A. K. and Stiglitz, J. E. (1977). Monopolistic competition and optimum product diversity. *The American economic review*, 67(3):297–308.

Donaldson, D. (2018). Railroads of the raj: Estimating the impact of transportation infrastructure. *American Economic Review*, 108(4-5):899–934.

Durán-Fernández, R. and Santos, G. (2014). Road infrastructure spillovers on the manufacturing sector in mexico. *Research in Transportation Economics*, 46:17–29.

Eaton, J. and Kortum, S. (2002). Technology, geography, and trade. *Econometrica*, 70(5):1741–1779.

Gandhi, A., Navarro, S., and Rivers, D. A. (2020). On the identification of gross output production functions. *Journal of Political Economy*, 128(8):2973–3016.

Gaubert, C. (2018). Firm sorting and agglomeration. *American Economic Review*, 108(11):3117–53.

Gibbons, C. E., Suárez Serrato, J. C., and Urbancic, M. B. (2018). Broken or fixed effects? *Journal of Econometric Methods*, 8(1):20170002.

Gibbons, S., Lyytikäinen, T., Overman, H. G., and Sanchis-Guarner, R. (2019). New road infrastructure: the effects on firms. *Journal of Urban Economics*, 110:35–50.

Hanson, G. H. (2005). Market potential, increasing returns and geographic concentration. *Journal of international economics*, 67(1):1–24.

Holl, A. (2016). Highways and productivity in manufacturing firms. *Journal of Urban Economics*, 93:131–151.

Holl, A. and Mariotti, I. (2018). Highways and firm performance in the logistics industry. *Journal of Transport Geography*, 72:139–150.

Hsieh, C.-T. and Klenow, P. J. (2009). Misallocation and manufacturing tfp in china and india. *The Quarterly journal of economics*, 124(4):1403–1448.

Kleinman, B., Liu, E., and Redding, S. J. (2023). Dynamic spatial general equilibrium. *Econometrica*, 91(2):385–424.

Lee, J. K. (2021). Transport infrastructure investment, accessibility change and firm productivity: Evidence from the seoul region. *Journal of Transport Geography*, 96:103182.

Levinsohn, J. and Petrin, A. (2003). Estimating production functions using inputs to control for unobservables. *The review of economic studies*, 70(2):317–341.

Levy, S. (2018). *Under-rewarded efforts: The elusive quest for prosperity in Mexico*. Inter-American Development Bank.

Lindenlaub, I., Oh, R., and Peters, M. (2022). Firm sorting and spatial inequality. Technical report, National Bureau of Economic Research.

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *econometrica*, 71(6):1695–1725.

OECD (2020). *Transport Bridging Divides*.

Olley, S. and Pakes, A. (1992). The dynamics of productivity in the telecommunications equipment industry.

Pérez, F. and Sandoval, A. (2017). Short-run market access and the construction of better transportation infrastructure in mexico. *Economía*, 18(1):225–250.

Redding, S. J. (2016). Goods trade, factor mobility and welfare. *Journal of International Economics*, 101:148–167.

Redding, S. J. and Turner, M. A. (2015). Transportation costs and the spatial organization of economic activity. *Handbook of regional and urban economics*, 5:1339–1398.

Shiferaw, A., Söderbom, M., Siba, E., and Alemu, G. (2015). Road infrastructure and enterprise dynamics in ethiopia. *The Journal of Development Studies*, 51(11):1541–1558.

Wan, G. and Zhang, Y. (2017). The direct and indirect effects of infrastructure on firm productivity: Evidence from manufacturing in the people's republic of china. Technical report, ADBI Working Paper.

Xu, M. and Feng, Y. (2022). How transportation infrastructure affects firm productivity? evidence from china. *China Economic Quarterly International*, 2(1):55–69.

Zerecero, M. (2021). The birthplace premium. Technical report, mimeo.

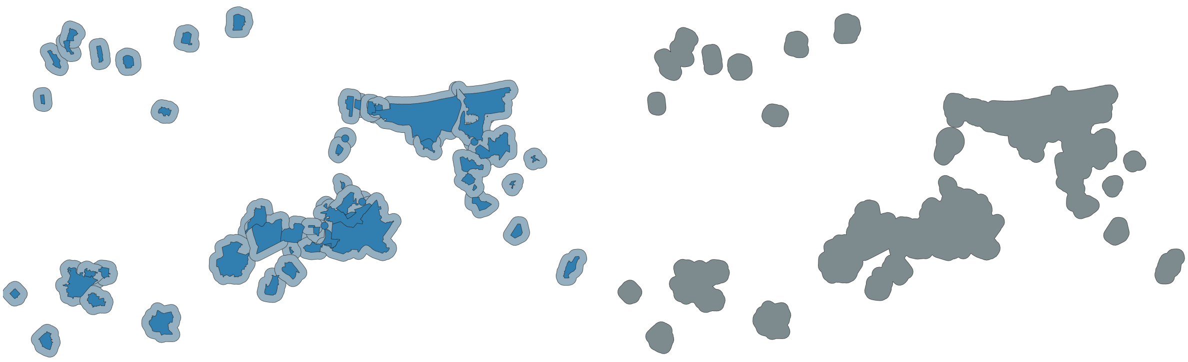
Zhou, J. (2023). The impacts of highways on firm size distribution: Evidence from china. *Growth and Change*, 54(2):482–506.

A Appendix: Data

Constant geography

Geographical units covered by the Economic Census of Mexico are States, Municipalities, Localities, and AGEBs, in descending order. To capture the change of economic activities within a single region over time, we needed to generate an identifier to overcome the issue of localities growing in size and splitting into multiple localities.[24] Therefore we developed a balanced panel of agglomerations, which we generate by combining neighboring localities that share borders. First, we take the 2019 Economic Census as a baseline considering that it will have the most extensive coverage of localities. The geographical coverage of the Economic Census is based on economic activity, hence a combination of both urban and rural localities. The next step was then to merge both the urban and rural localities that appeared in the Census into the shapefiles published by the INEGI. However, in cases where we were not able to find a shapefile for a locality in the Census, we found an alternative source of the Catalog, also published by INEGI which is a list of localities and their coordinates. We transformed the list of coordinates into points on the map and created a 1km buffer around those points in order to factor them in as polygons. With the selected set of localities' polygons, we create a buffer of 1km to identify clusters of localities. If the buffered localities share borders, we define it as an "Agglomeration". This process yielded a total of 3,248 unique agglomeration IDs.

Figure 12: Constructing agglomerations



(a) 1km Buffer around localities (b) Grouped neighboring localities

Notes: Figure shows an arbitrary area.

Once we had the polygon shapefile of agglomeration IDs, we assigned each year of localities in the respective Economic Census to a respective agglomeration id. This process is conducted in three steps. First, we repeat the process of selecting from the map which localities are covered by the Census. We then overlap the localities shapefile with the agglomeration shapefile to assign the ID of its overlapping agglomeration. For the localities that were not matched to the Economic Census, the second source was the Catalog, and for those that still did not find a correspondence, we assigned the same agglomeration id as the largest locality in the given municipality.

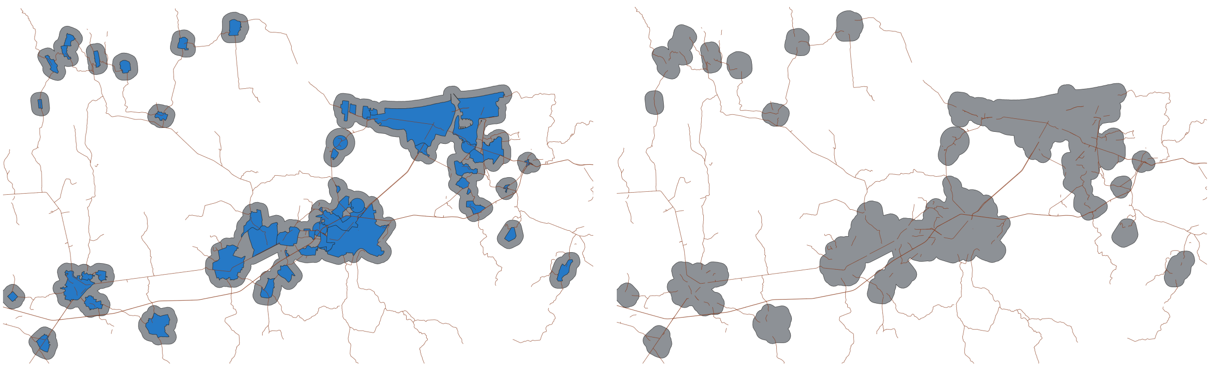
[24]Localities are defined as 2,500 inhabitants.

Roads

We use 2004, 2011, 2014, and 2019 highways (*Red Nacional de Caminos*) publicly available from INEGI. Among the different types of road constructions, we focus on intercity highways (Carreteras). Similar to agglomerations, we follow the assumption that highways cannot disappear. Therefore, we fixed the set of highways from each year by adding highways that existed in the previous year but were omitted. First, we created a buffer of 500m around all the highway maps to accommodate inconsistent breaks of highways. Next, we overlap the previous year's map with the more recent map, identifying which segments lie outside the buffer zones of the most recent map. This will locate the highways that exist in the previous year but not on the most recent map. Based on the assumption that highways do not disappear, we append these parts to the recent map and create a "fixed" map of highways.

The information available for each highway are the ID number of the highway, route number, speed, and the number of lanes.

Figure 13: Highways in 2018



(a) 1km Buffer around localities (b) Grouped neighboring localities

Notes: Figure shows an arbitrary area.

Table 13: National investment in highways (Million 2018 MXN)

	2004-2014	2014-2018
Total investment	599650.42	221466.46
Yearly avg.	59965.04	55366.61

Investment numbers taken again from the annuals. We take half the reported investment for end-of-period and start-of-period years. Yearly values deflated with the inflation reported between July of the base year and July of 2018. Inflation taken from INEGI's inflation calculator available at https://www.inegi.org.mx/app/indicesdeprecios/calculadorainflacion.aspx.

Minimum travel times

Similar to grid points, but in more accurate distance measurement, we use Uber's Hexagonal Hierarchical Spatial Index as our grid system, or in other words, cells.[25]

[25]https://www.uber.com/blog/h3/

Based on the hexagonal system, we locate agglomerations and highway networks to the overlapping hexagon and store the highway's information in the respective hexagons. For instance, information on the speed, number of lanes, and width of the road will be stored in the neighboring hexagons, which allows us to develop an algorithm to estimate travel times that follow the path of hexagons. In addition to the highway information publicly available at INEGI, we consider the elevation of localities to reflect actual travel times.[26]

Our travel time analysis is conducted in four steps. First, we select the origin, destination, and highway network that will be used to travel from one location to another. It can be traveling from one agglomeration to another, or it could also be from one agglomeration to an airport, port, or even a specific city. For the origin and destination shapefiles, in case they are in polygons, we extract each polygon's centroids and consider them as a starting point and an ending point. Once we have chosen the shapefiles, we use the aforementioned open-source hexagon system by Uber to locate the shapefiles into respective hexagons. When storing information to the highways, we assign a set of parameters to address the issue of missing information for some years. We acknowledge that some highway shapefiles might not have all the information on speed, lanes, and width; hence we include in the algorithm to take specific values when there is a piece of missing information. Additionally, there will always be hexabins where it is not close to a highway network. For these hexagons, we assign a speed value of 5km/hour, meaning the only option will be to travel by walking. We also assign the order of variables based on priorities among speed, lane, and width for the code to first use when calculating the travel time. Then, we estimate the travel time from one origin point to all other destinations using the properties. Finally, we merge all the different origin points into a single matrix.

Construction plans

We focus on two government infrastructure projects under two administrations: Felipe Calderón(2006-2012) (see Figure 14) and Enrique Peña Nieto(2012-2018) (see Figure 15). Based on the official report National Infrastructure Program published by the Department of Transportation (Sector Comunicaciones y Transportes(SCT)), we focused on highway plans, which yielded 175 plans from the Calderón administration and 76 plans from the Peña Nieto administration. Both reports include details on which State the highway is located in, and the type of improvement the plan aims to achieve (construction or expansion).

[26]https://portal.opentopography.org/datasetMetadata?otCollectionID=OT.042013.4326.1

Figure 14: Example of 2007-2012 Construction Plan

Carreteras Región Noroeste

Nombre / descripción	Entidad federativa	Monto total de inversión (miles de millones de pesos)	Fuente / esquema de financiamiento	Fecha de realización	
				Inicio	Término
Caborca-Sonoyta-San Luis Río Colorado-Mexicali					
Caborca-Sonoyta Ampliación a 12 metros (143.1 km)	Sonora	1.2	PEF	2006	2010
Sonoyta-San Luis Río Colorado Ampliación a 12 metros (192 km)	Sonora	1.4	PEF	2008	2011
San Luis Río Colorado-Mexicali Ampliación a 4 carriles (56 km)	Baja California	1.7	PEF	2006	2008
Ciudad Obregón-Hermosillo-Nogales					
Libramiento de Ciudad Obregón Construcción a 12 metros (45 km)	Sonora	0.7	Aprovechamiento de activos	2010	2011
Estación Don-Nogales Ampliación a 4 carriles (468.5 km)	Sonora	2.5	Aprovechamiento de activos	2010	2011
Libramiento de Hermosillo Construcción a 12 metros (37 km)	Sonora	0.9	Aprovechamiento de activos	2010	2011
Transpeninsular de Baja California					
Maneadero-Punta Colonet Ampliación a 12 metros (105 km)	Baja California	0.5	PEF	2009	2010
La Purísima-San Ignacio Ampliación a 12 metros (180 km)	Baja California Sur	2.0	PEF	2009	2012

Carreteras Región Noroeste

Nombre / descripción	Entidad federativa	Monto total de inversión (miles de millones de pesos)	Fuente / esquema de financiamiento	Fecha de realización	
				Inicio	Término
La Paz-Los Cabos					
Puentes paralelos El Piojito en La Paz Construcción a 4 carriles	Baja California Sur	0.1	PEF	2007	2008
La Paz-San Pedro Construcción a 4 carriles (15.5 km)	Baja California Sur	0.3	PEF	2007	2008
San Pedro-Todos Santos Ampliación a 12 metros (52 km)	Baja California Sur	0.5	PEF	2008	2009
Libramiento de Todos Santos Construcción a 12 metros (10 km)	Baja California Sur	0.3	PEF	2008	2009
Todos Santos-Cabo San Lucas Ampliación a 12 metros (73 km)	Baja California Sur	1.2	PEF	2007	2010
Mexicali-Laguna de Chapala					
Mexicali-San Felipe Ampliación a 12 metros y 4 carriles (150 km)	Baja California	1.1	PEF	2009	2012
Puertecitos-Laguna de Chapala Ampliación a 7 metros (110 km)	Baja California	0.6	PEF	2008	2010
Mazatlán-Culiacán					
Libramiento de Mazatlán Construcción a 12 metros (31 km)	Sinaloa	1.0	Aprovechamiento de activos	2009	2010
Libramiento de Culiacán Construcción a 12 metros (22 km)	Sinaloa	0.7	Aprovechamiento de activos	2009	2010

Figure 15: Example of 2013-2018 Construction Plan

Entidad Nombre de la obra	Inversión (MP)	Meta (km)	Tipo de Trabajo
SONORA			
Caborca-Sonoyta	66.8	8.6	Ampliación
Santa Ana-Altar 1/	0.0	1.7	Ampliación
Blvd. Álvaro Obregón en la Cd. Nogales	4.5	0.0	Ampliación
Puente Cabullona	5.0	0.0	Ampliación

Plan **Current progress**

Based on the construction plans, we develop a data set that contains information on the respective state in which the plan takes place, the duration of the project, and specific details of the construction.

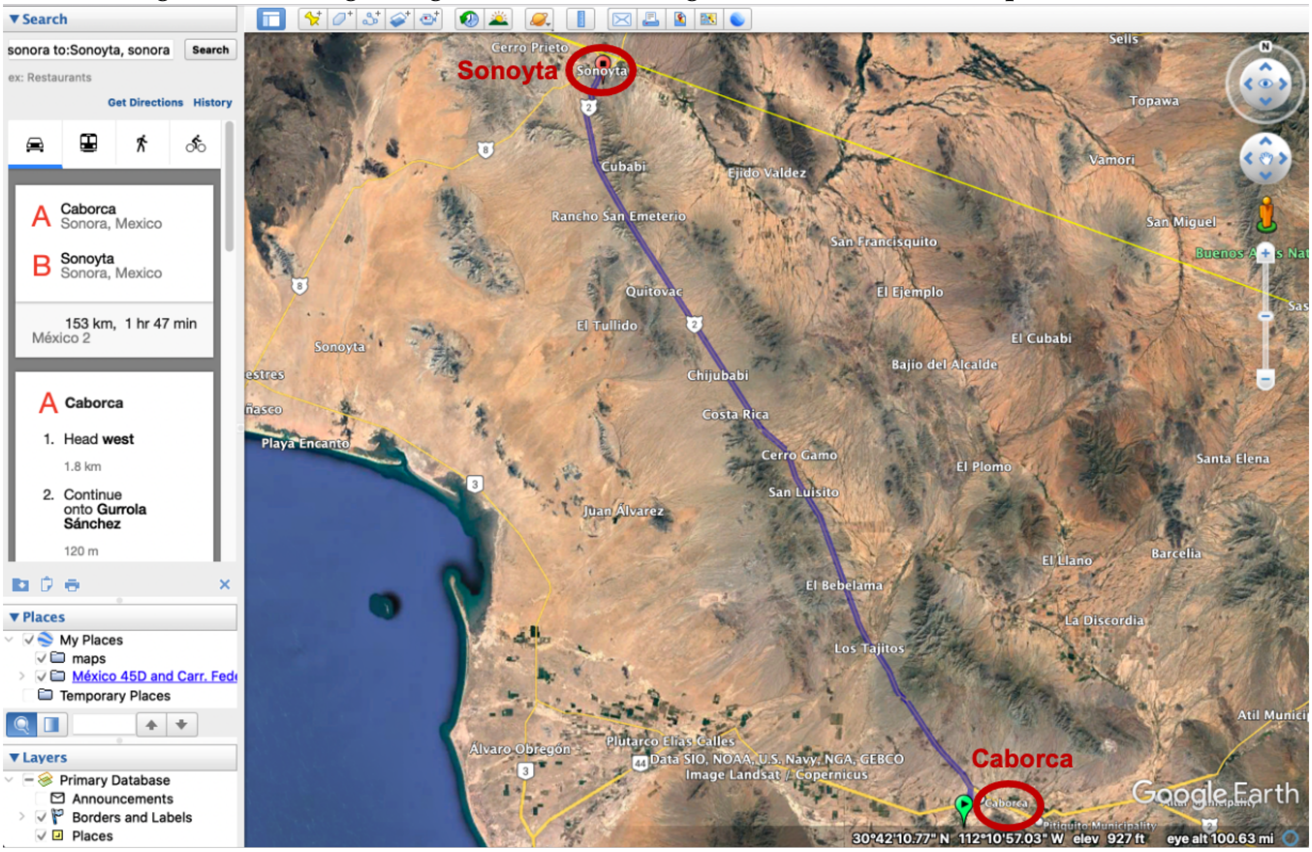


Figure 16: Using Google Earth Pro to digitize the construction plans

Once we had a dataset of the construction plans list, the next step was to digitize the information in map format. Using Google Earth, we set the origin and destination of the highway plan based on how the name is written (e.g., if the plan stated "Expansion a 12 m Caborca-Sonoyta", meaning expand the lane to 12m in the highway connecting Caborca and Sonoyta, we would set Caborca as the origin and Sonoyta as the destination). Each search was saved, merged, then exported into a shapefile. However, note that the plans did not mention which specific part of the highway they will improve. Thus we considered the entire highway as a part of the plan. Once we had a complete shapefile of all the construction plans, we conducted a quality check for all the plans. We would search the plan online and see if there are additional sources published by each State government supplementing the details of the plan. In some cases, the State government reported an image of the exact location of the plan.

We were able to classify the construction plans based on the type of road, the type of improvement, and whether the targeted highways are located in/out of a city.

Type of highways listed in the construction plan:

- Inter-region (e.g., Chalco-Nepantla)
- Beltways (e.g., Libramiento)
- Connection to the border of each state (e.g., Límite de estados Pue/Ver)
- Junctions (e.g., entronque La Ventosa)

- Access to a specific location (e.g.,Acceso al Puerto Salina Cruz)
- Bridges (e.g., Puente)

Type of construction plans:

- Expand highways to 4/6/8 lanes (both direction)
- Construct 4 lanes (both directions)
- Expand or construct 2 lanes and 2 side roads
- Modernize and improve conditions

City classification:

- IN: If the construction plan is for a highway inside a city
- OUT: If the construction plan is for a highway connecting two regions outside a city
- LIB: If the construction plan is for beltways specifically [27]

Collecting information on whether the construction plan was executed.

Treatment variables

Variables For all the treatment variables, we generate three types of buffers around each agglomerations in order to accommodate the noise of map accuracy. All variables are constructed by agglomeration IDs.

Length of highways' segments that overlap each agglomeration Area of buffered agglomerations Density (length/area) of highways' segments

With regard to the construction plan, we first construct a dummy variable indicating whether an agglomeration lies within any construction plan. We assess by 5,10, and 15km buffers of each agglomeration. Next, we specify the construction plan by those that were executed and those that were not. We generate a dummy variable indicating whether an agglomeration lies within an executed construction plan and a non-executed plan. Lastly, we develop a dummy variable indicating whether an agglomeration is placed in a construction plan's starting and end points. We identify the starting and end point by the region's first and last name mentioned in the plan.

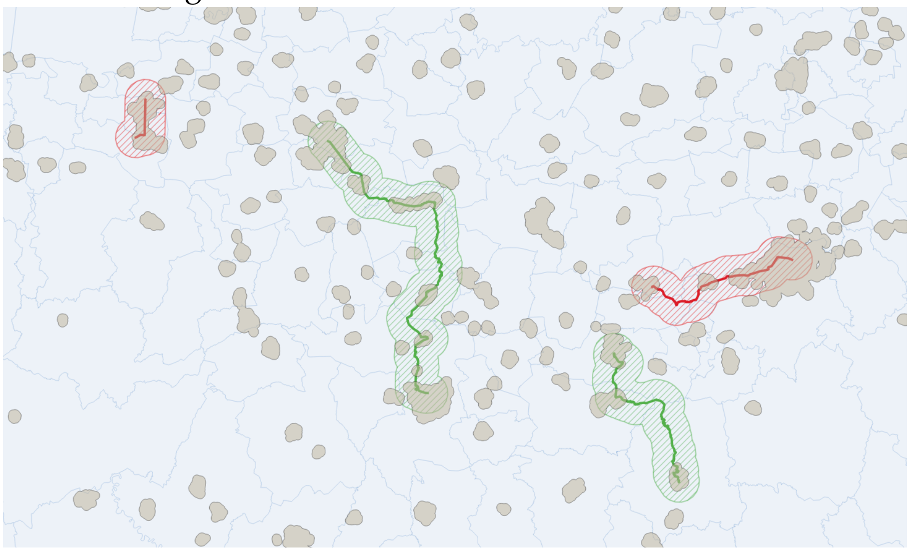
We also construct treatment variables to measure market access. Using the population census of 2019, we extract the population size by agglomerations. Next, we identify the top 100 agglomerations with the largest population. Then we use the previously generated minimum travel time values to generate a new variable, the distance from each agglomeration to the nearest hub.

[27] We specify the beltways since beltways mostly have the purpose of reducing traffic within each city.

B Appendix: Empirics

Treatment and sample

Figure 17: Treated and untreated locations



Notes: Figure displays an arbitrary area of the country. Gray areas are locations (3,248 in total). Dashed areas are buffers around construction plans. For a given year, green construction plans have been fully executed and red not yet.

Table 14: Treated locations

(a) Locations by overlap with plans

	2007-2012			2013-2018		
Buffer size (km)	5	10	15	5	10	15
With plans	771	1,052	1,330	457	678	898
With out plans	2,475	2,194	1,916	2,789	2,568	2,348
Total	3,246	3,246	3,246	3,246	3,246	3,246

(b) Locations by execution of plans

	2007-2012			2013-2018		
Buffer size (km)	5	10	15	5	10	15
Executed	259	261	265	278	404	551
Not executed	512	791	1,065	179	274	347
Total	771	1,052	1,330	457	678	898

Table 15: Firms in the sample and treated group

(a) Sample of firms

	2007-2012			**2013-2018**			
Buffer size (km)	5	10	15	5	10	15	Total
1998	2.09	2.16	2.26	1.65	1.69	1.73	2.78
2003	2.23	2.30	2.42	1.75	1.79	1.84	2.98
2008	2.72	2.81	2.96	2.14	2.20	2.27	3.67
2013	3.06	3.17	3.36	2.43	2.50	2.58	4.17
2018	3.43	3.56	3.78	2.73	2.81	2.92	4.74

(b) Treated firms

	2007-2012			**2013-2018**			
Buffer size (km)	5	10	15	5	10	15	Total
1998	1.43	1.50	1.52	0.73	0.76	0.80	2.78
2003	1.51	1.59	1.61	0.77	0.80	0.84	2.98
2008	1.82	1.92	1.95	0.97	1.01	1.07	3.67
2013	2.04	2.16	2.20	1.12	1.16	1.23	4.17
2018	2.26	2.40	2.45	1.26	1.31	1.40	4.74

Validity of empirical approach

Table 16: Predicting construction plans 2013-2018

	(1) Plan	(2) Execution
log(population)	0.0483***	-0.0262
	(0.00987)	(0.0173)
log(value added/workers)	0.0563***	0.0483
	(0.0138)	(0.0251)
Δ log(population)	0.384***	0.144
	(0.0566)	(0.104)
Δ log(value added/workers)	-0.0335*	-0.0123
	(0.0147)	(0.0287)
log(votes for PRI)	-0.0191*	-0.0191
	(0.00828)	(0.0149)
Observations	2146	611
R-sq	0.255	0.379

Notes: Standard errors are in brackets. $^{***}p < 0.01$,$^{**}p < 0.05$,$^{*}p < 0.1$. Regressions at the municipality level. Variables and growth rates are from Economic Census 2003 and 2008 and population Census 2000 and 2010.

Table 17: Balance table

Variable	Locat.	Mean untreated	Mean treated	Diff.	s.e.	p-value	Stat. signif.
Share manuf.	400	0.169	0.151	-0.018	0.015	0.220	
Share salaried	400	0.228	0.288	0.061	0.019	0.001	***
log(K)	400	11.237	11.547	0.310	0.310	0.318	
log(K/L)	400	4.305	4.527	0.223	0.109	0.041	**
Δ share manuf.	376	0.018	0.013	-0.006	0.007	0.407	
Δ share salaried	376	-0.019	-0.025	-0.006	0.012	0.612	
Δ K	376	0.441	0.445	0.004	0.074	0.957	
Δ K/L	376	-0.001	0.072	0.073	0.067	0.275	
log(L per estab.)	400	0.944	0.996	0.052	0.049	0.289	
log(V.A./L)	400	4.665	4.859	0.194	0.138	0.161	
log(TFP) (L-P)	400	4.028	4.258	0.229	0.128	0.073	*
Δ L per estab.	376	0.114	0.082	-0.032	0.027	0.229	
Δ V.A./L	376	-0.202	-0.260	-0.058	0.065	0.373	
Δ TFP	376	-0.177	-0.170	0.007	0.094	0.937	
log(population)	397	10.949	10.964	0.015	0.174	0.931	
Δ population	362	0.801	0.832	0.030	0.015	0.050	*
log(highways)	400	10.753	10.618	-0.136	0.093	0.147	
Δ highways	400	0.271	0.236	-0.036	0.023	0.114	

First stage regressions

Construction plans and market access. An implicit assumption of our identification strategy is that the execution of construction plans affects firms by increasing their market access as they can reach more distant markets or acquire intermediate inputs at a lower cost. We test this assumption by estimating the following two-ways-fixed-effects model:

$$log(MA_j) = time + treatment_j + \delta \cdot time \cdot treatment_j + \beta \cdot controls_j + \varepsilon_j \tag{45}$$

We estimate Equation 45 separately for both sets of construction plans at the location level. Here $time$ denotes pre and post treatment periods and $treatment_j$ whether the location belongs to the treatment group or not. $controls_j$ is a battery of locaiton level controls at baseline.

MA_i is a measure of market access. We follow Allen and Arkolakis (2014); Blankespoor et al. (2017) to compute it according to:

$$log(MA_i) = \sum_j \frac{Population_j}{\tau_{i,j}^{\sigma-1}} \tag{46}$$

To stay consistent with the literature, we assume $\sigma = 9$. MA_i captures the market access from location i, defined as the weighted sum of the population of all locations in the country discounted by the one-to-one trade costs τ_{ij}. For this exercise, we keep the population fixed at 2003 levels. We compute two versions of this measure. MA_1 that includes all locations; and MA_2, that includes all but the location i itself. The trade costs τ_{ij} is determined as in Equation 30, explained in detail in the model section.

Table 18: First stage regressions

Plans 2007-2012			Plans 2013-2018		
	(1) $log(MA_1)$	(2) $log(MA_2)$		(3) $log(MA_1)$	(4) $log(MA_2)$
time	0.00752***	0.00812***	time	0.00130***	0.00154***
	(0.00180)	(0.00163)		(0.000188)	(0.000125)
treated	-0.00439*	-0.00383	treated	-0.000180	-0.000397
	(0.00245)	(0.00236)		(0.000625)	(0.000576)
time*treated	0.00798*	0.00757*	time*treated	0.000756**	0.000560*
	(0.00448)	(0.00444)		(0.000357)	(0.000329)
Controls	Yes	Yes	Controls	Yes	Yes
Obs.	1230	1230	Obs.	750	750
R-sq	0.99	0.99	R-sq	0.99	0.99

Notes: Standard errors are in brackets. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table 18 shows the results for both sets of construction plans, for two measures of market access and controlling for baseline characteristics market access in 2004 and state fixed effects. In summary, execution of construction plans has a positive effect on market access in treated locations.

For the construction plans 2007-2012, their execution implied a 0.79% higher market access for exposed locations. In this period, market access increased in average 0.75% for all locations, meaning that the treatment implied an increase in market access twice as large for treated locations. For the 2013-2018 plans, the increase was 0.07%. Since in this period market access increased in average 0.13% for all locations, the treatment implied a 53% larger market increase for treated locations.

Robustness checks

Regressions by sector

Table 19: Regressions by sector, Construction plans 2007-2012

Manufacturing

	(1) $log(va/L)$	(2) $log(TFP)_{GNR}$	(3) $log(L)$	(4) $log(w)$	(5) $Entry$	(6) $Exit$
β_{-1}	.0733*	0.01	0.0226	0.0062	0.0084	.0203*
s.e.	[.0401]	[.0148]	[.022]	[.0107]	[.0117]	[.0121]
β_0	-.0463*	0.0091	-.0559***	-0.0056	0.008	-.0199***
s.e.	[.0237]	[.0066]	[.0161]	[.0064]	[.0092]	[.0059]
β_1	.0648*	0.0129	-.0555*	-0.0107	0.0099	-.0337***
s.e.	[.0342]	[.0144]	[.0287]	[.0073]	[.0134]	[.0082]
Controls	No	No	No	No	No	No
Obs.	733,654	733,654	733,654	733,654	733,654	733,654

Commerce

	(1) $log(va/L)$	(2) $log(TFP)_{GNR}$	(3) $log(L)$	(4) $log(w)$	(5) $Entry$	(6) $Exit$
β_{-1}	-0.0372	-0.014	-0.0029	-0.0054	0.0099	0.0099
s.e.	[.023]	[.0158]	[.0071]	[.006]	[.0062]	[.0084]
β_0	0.0178	0.0092	-0.0116	-0.0045	0.0048	-.0144**
s.e.	[.0118]	[.0078]	[.0082]	[.0057]	[.0059]	[.0067]
β_1	.0835***	.0361**	-0.0055	-.0153**	0.0056	-.029**
s.e.	[.0235]	[.016]	[.009]	[.0073]	[.0049]	[.0137]
Controls	No	No	No	No	No	No
Obs.	2,727,356	2,727,356	2,727,356	2,727,356	2,727,356	2,727,356

Services

	(1) $log(va/L)$	(2) $log(TFP)_{GNR}$	(3) $log(L)$	(4) $log(w)$	(5) $Entry$	(6) $Exit$
β_{-1}	-0.03	-0.0081	-0.004	-0.0069	0.0082	0.003
s.e.	[.0258]	[.0097]	[.0104]	[.0064]	[.0089]	[.0086]
β_0	-0.0015	0.0038	-.017**	-0.0013	0.021	-.0203**
s.e.	[.021]	[.0045]	[.0069]	[.0058]	[.0141]	[.0096]
β_1	.0533***	.0188**	-0.0019	-.0108*	.0217***	-.0388***
s.e.	[.0202]	[.0095]	[.0123]	[.0058]	[.0075]	[.0143]
Controls	No	No	No	No	No	No
Obs.	3,511,463	3,511,463	3,511,463	3,511,463	3,511,463	3,511,463

Notes: Standard errors are in brackets. $^{***}p < 0.01,^{**}p < 0.05,^{*}p < 0.1$.

Table 20: Regressions by sector, Construction plans 2013-2018

Manufacturing

	(1) $log(va/L)$	(2) $log(TFP)_{GNR}$	(3) $log(L)$	(4) $log(w)$	(5) $Entry$
β_{-1}	-0.0505	-0.0127	0.0344	0.0036	0.0114
s.e.	[.0478]	[.0158]	[.0219]	[.0068]	[.0085]
β_0	0.0351	0.0092	0.0214	.0199**	-0.0009
s.e.	[.048]	[.0156]	[.0319]	[.0079]	[.0109]
β_1	-.1506**	-.0628***	0.0378	-0.0128	0.029
s.e.	[.0587]	[.024]	[.0263]	[.012]	[.0241]
Controls	No	No	No	No	No
Obs.	645,540	645,540	645,540	645,540	645,540

Commerce

	(1) $log(va/L)$	(2) $log(TFP)_{GNR}$	(3) $log(L)$	(4) $log(w)$	(5) $Entry$
β_{-1}	-.0562**	-.0182*	-0.0084	0.0048	0.009
s.e.	[.0222]	[.0102]	[.0056]	[.0035]	[.0057]
β_0	.0362**	.0173*	.0198*	.0081**	-0.0018
s.e.	[.0158]	[.01]	[.0102]	[.0036]	[.0076]
β_1	-.0438*	-0.0107	.0343***	0.0088	0.0171
s.e.	[.0247]	[.0186]	[.0088]	[.0131]	[.0105]
Controls	No	No	No	No	No
Obs.	2,521,552	2,521,552	2,521,552	2,521,552	2,521,552

Services

	(1) $log(va/L)$	(2) $log(TFP)_{GNR}$	(3) $log(L)$	(4) $log(w)$	(5) $Entry$
β_{-1}	-.0652**	-.0182**	-0.0067	0.002	0.0074
s.e.	[.0298]	[.0084]	[.0103]	[.0056]	[.0065]
β_0	.078**	.0207**	0.0111	.0098*	0.0049
s.e.	[.0312]	[.0099]	[.007]	[.0059]	[.0082]
β_1	.0811***	.0209***	.0337***	0.0231	.0287**
s.e.	[.0233]	[.0073]	[.0129]	[.0145]	[.0135]
Controls	No	No	No	No	No
Obs.	3,144,586	3,144,586	3,144,586	3,144,586	3,144,586

Notes: Standard errors are in brackets. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Regressions with controls

Table 21: Regressions with controls. Construction plans 2007-2012

	(1) log(va/L)	(2) log(TFP) (GNR)	(3) log(L)	(4) log(w)	(5) Entry	(6) Exit
β_{-1}	-0.025	-0.0097	-0.0003	-0.0054	0.0097	0.0074
s.e.	[.0209]	[.0102]	[.0078]	[.0044]	[.0069]	[.0071]
β_0	0.0095	.009**	-.0143***	-0.0007	0.0141	-.0173**
s.e.	[.0125]	[.0044]	[.0054]	[.0038]	[.0102]	[.0072]
β_1	.0748***	.0295***	-0.0021	-.0106**	.0152***	-.0329**
s.e.	[.0216]	[.011]	[.0069]	[.0045]	[.005]	[.0131]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	7,060,649	7,060,649	7,060,649	7,060,649	7,060,649	7,060,649

Notes: Standard errors are in brackets. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$. Sample includes all firms from 1998 to 2018. Excludes firms with value added or capital smaller than zero. Controls include 3-digit sector.

Table 22: Regressions with controls. Construction plans 2013-2018

	(1) log(va/L)	(2) log(TFP) (GNR)	(3) log(L)	(4) log(w)	(5) Entry
β_{-1}	-.0629***	-.0193***	-0.0062	0.0037	0.0099
s.e.	[.0239]	[.0072]	[.0078]	[.0046]	[.0066]
β_0	.0494**	.0156**	.0134*	.0089**	0.0018
s.e.	[.0205]	[.0069]	[.0079]	[.0038]	[.0076]
β_1	-0.0033	-0.005	.0258***	.0129*	.025**
s.e.	[.0219]	[.0095]	[.0094]	[.0069]	[.0125]
Controls	Yes	Yes	Yes	Yes	Yes
Obs.	6,375,668	6,375,668	6,375,668	6,375,668	6,375,668

Notes: Standard errors are in brackets. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$. Sample includes all firms from 1998 to 2018. Excludes firms with value added or capital smaller than zero. Controls include 3-digit sector.

Regressions by buffer size

Table 23: Buffer = 10km, Construction plans 2007-2012

	(1) log(va/L)	(2) log(TFP) (GNR)	(3) log(L)	(4) log(w)	(5) Entry	(6) Exit
β_{-1}	-.0414*	-0.0177	-0.0059	-0.0082	.0118*	0.0003
s.e.	[.0217]	[.0123]	[.008]	[.0051]	[.0063]	[.0072]
β_0	0.0059	0.0092	-0.0119	-0.0014	0.0148	-.0138*
s.e.	[.0209]	[.0077]	[.0074]	[.0053]	[.0092]	[.0079]
β_1	.0598***	.0152*	-0.0059	-.0132**	.0191***	-.0334***
s.e.	[.0211]	[.0088]	[.0095]	[.0053]	[.0043]	[.0128]
Controls	No	No	No	No	No	No
Obs.	7,280,866	7,280,866	7,280,866	7,280,866	7,280,866	7,280,866

Notes: Standard errors are in brackets. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table 24: Buffer = 10km, Construction plans 2013-2018

	(1) log(va/L)	(2) log(TFP) (GNR)	(3) log(L)	(4) log(w)	(5) Entry
β_{-1}	-.065**	-0.0078	-0.004	0.0024	0.0078
s.e.	[.0265]	[.0076]	[.0074]	[.0049]	[.0054]
β_0	.0564**	.0184***	.0154*	.0108**	0.0017
s.e.	[.0221]	[.0071]	[.0089]	[.0048]	[.0077]
β_1	0.0116	0.0133	.0372***	.0148**	.0277**
s.e.	[.0241]	[.0105]	[.0101]	[.0062]	[.0119]
Controls	No	No	No	No	No
Obs.	6,526,519	6,526,519	6,526,519	6,526,519	6,526,519

Notes: Standard errors are in brackets. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table 25: Buffer = 15km, Construction plans 2007-2012

	(1) log(va/L)	(2) log(TFP) (GNR)	(3) log(L)	(4) log(w)	(5) Entry	(6) Exit
β_{-1}	-0.0351	-0.0143	-0.004	-0.0075	.0111*	0.0038
s.e.	[.0217]	[.012]	[.0076]	[.0047]	[.0061]	[.0072]
β_0	0.0013	0.0083	-0.0109	-0.0007	.0161*	-0.0117
s.e.	[.0191]	[.007]	[.0077]	[.0051]	[.0088]	[.0076]
β_1	.0522**	0.0138	-0.002	-.0126**	.0216***	-.0284**
s.e.	[.0211]	[.0084]	[.0098]	[.005]	[.0045]	[.0132]
Controls	No	No	No	No	No	No
Obs.	7,665,879	7,665,879	7,665,879	7,665,879	7,665,879	7,665,879

Notes: Standard errors are in brackets. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table 26: Buffer = 15km, Construction plans 2013-2018

	(1) log(va/L)	(2) log(TFP) (GNR)	(3) log(L)	(4) log(w)	(5) Entry
β_{-1}	-.0718***	-0.0089	-0.0042	0.0036	0.0076
s.e.	[.0255]	[.0075]	[.0076]	[.0048]	[.0053]
β_0	.0611***	.0183***	.015*	.0096**	0.0023
s.e.	[.0217]	[.007]	[.0084]	[.0047]	[.0075]
β_1	0.0137	0.0131	.0361***	.0147**	.029**
s.e.	[.0238]	[.0102]	[.0098]	[.0061]	[.0117]
Controls	No	No	No	No	No
Obs.	6,723,947	6,723,947	6,723,947	6,723,947	6,723,947

Notes: Standard errors are in brackets. $^{***}p < 0.01, ^{**} p < 0.05, ^{*} p < 0.1$.

Evidence on firm mobility, 2013-2018

In this section we show a novel margin of firm dynamics that can be affected by the development of the highways network: the geographical location of firms within cities. First, we show that firm mobility is present in the data by exploiting a novel section in the Economic Census 2018 where establishments are asked if they had a different location in the previous wave (2013), and then report the main reason why they moved. And second, by regressing the mobility decision and reasons on execution of construction plans.

Firm mobility in the data. The 2018 census included two new questions regarding firm mobility. First, the census asks if the firm changed address between 2013 and 2018. If the answer is yes, the census asks an additional question on the reason why it moved to a different address. The reasons are codified in 6 categories: low business growth, increase in facility's rental prices, to move closer to clients and suppliers, public insecurity, tax-related reasons and, finally, other reasons.

Not all firms answered the firm mobility questions. The 2018 census covers 4,737,931 firms; among them, 1,832,685 answered the mobility questions, which is 39% of the total. According to INEGI's officials, small and medium firms are over-represented among the respondent firms. Considering only the respondents, 4.28% of firms changed address between 2013 and 2018, which means that the census documents 78,527 movers. By extrapolating this percentage to the full census, the number of movers could be around 203,011 firms. However, this number could be biased if non-respondents have a different moving behavior.

Among the 78,527 movers, 12.6% are from the manufacturing sector, 32.6% from commerce, and 54.8% from services. In the population of firms, 12.3% are in the manufacturing sector, 47.6% in commerce, and 40.1% in services. If moving to a different location was random, we should expect these percentages to be similar. However, there is a large disparity in the share of movers from the services sector and the share they represent in the population. This suggests that service providers are more likely to move to another location. A possible explanation could be that they face lower moving costs or expect higher returns from moving than firms in commerce and manufacturing.

Firms might have many reasons to move. The Economic Census asks what is the main one and codifies the answers. The distribution of these answers is the following. 10.43% declare low business growth, 31.8% increase in facility's rental prices, 13.8% to move closer to clients and suppliers, 3.6% public insecurity, 0.8% tax-related reasons and, finally, 39.5% other reasons.

The effects of better highways on firm mobility. We now provide evidence on the effects of highways on the firm mobility decision. To do this, we estimate the following probit model:

$$P(\text{new location in 2018 = yes})_{ij} = \Phi[\alpha + \beta \mathbf{X}_{ij} + \delta D_j + \varepsilon_{ij}] \tag{47}$$

In this model, i denotes the firm and j the location. $\mathbf{X}_{ij}$ denotes a vector of controls, and D_j takes the value of 1 if construction plans were executed between 2013 and 2018 and zero otherwise. The parameter of interest is δ, which captures whether better highways affect the probability of moving to a different location.

Table 27 shows the results by sector and with and without controls for population density and number of firms and workers at baseline, to control for the fact that mobility might defer depending on how crowded a location is. Columns (1) and (2) show that execution of contraction plans has a positive effect on the probability of an firm to have moved to a different location between census waves of 2013 and 2018. Columns (3) and (4) show that manufacturing firm mobility doesn't seem to be connected to changes in the highways network. Finally, firms in the services sector seem to be affected by highways when they make mobility decisions but these effects are not robust to baseline demographic characteristics of the location.

Table 27: Porbit model. Outcome: probability of moving

Sector	**Commerce**		**Manufacturing**		**Services**	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	.1269**	.0731**	0.0907	0.0699	.0992**	0.0595
se	-0.0484	-0.0349	-0.0552	-0.0552	-0.0497	-0.04
N	475,370	472,852	124,885	124,464	476,515	476,031
Controls	No	Yes	No	Yes	No	Yes

Notes: Standard errors are in brackets. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Similarly, to determine if highways affect the reasons why firms move, we run the following probit model:

$$P(\text{main reason } r = \text{yes})_{ij} = \Phi[\alpha + \beta \mathbf{X}_{ij} + \delta D_j + \varepsilon_{ij}] \tag{48}$$

Where r is the main reason why the firm changed location and can be: low business growth, increase in facility's rental prices, to move closer to clients and suppliers, public insecurity, tax-related reasons and, finally, other reasons. Table 28 shows the results by sector and adding controls for baseline demographic characteristics such as population density, number of firms and workers. Whereas firms can move for diverse reasons, when highways are improved, the reported reason that is positively distorted is proximity to clients and suppliers, except for the manufacturing sector.

Table 28: Porbit model. Outcome: probability of moving

Commerce						
	(1)	(2)	(3)	(4)	(5)	(6)
Reason	Growth	Rents	Proximity	Insecurity	Taxes	Other
Treatment	-0.0045	-0.0693	.1113**	0.077	0.1018	-0.0097
se	[.0376]	[.0632]	[.0434]	[.0648]	[.0705]	[.0543]
N	14,672	14,672	14,672	14,672	14,672	14,672
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Manufacturing						
	(1)	(2)	(3)	(4)	(5)	(6)
Reason	Growth	Rents	Proximity	Insecurity	Taxes	Other
Treatment	-0.0023	-0.006	0.0392	0.0226	.3036**	-0.021
se	[.0498]	[.0714]	[.0558]	[.0704]	[.112]	[.072]
N	5,802	5,802	5,802	5,802	5,802	5,802
Controls	Yes	Yes	Yes	Yes	Yes	Yes

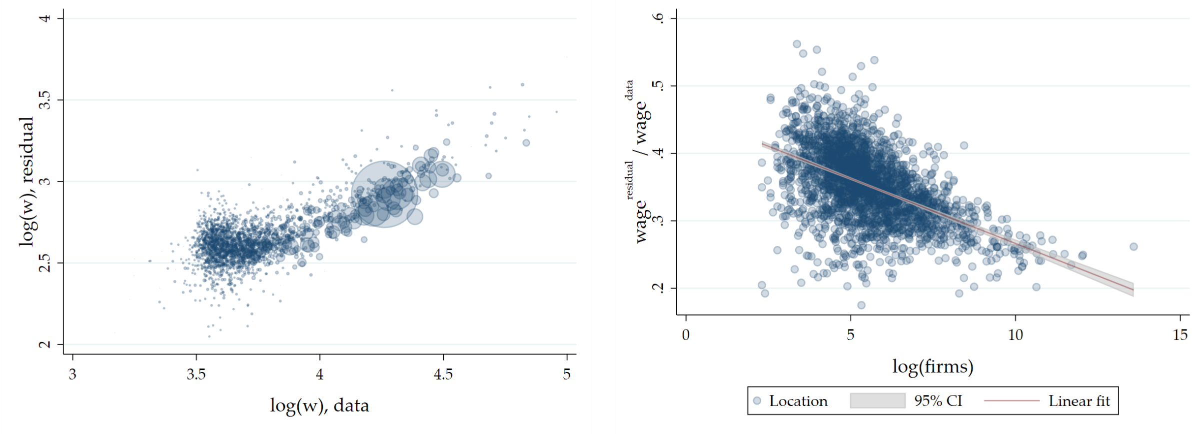
Services						
	(1)	(2)	(3)	(4)	(5)	(6)
Reason	Growth	Rents	Proximity	Insecurity	Taxes	Other
Treatment	0.0007	-0.0771	.1241***	0.0441	0.086	-0.0073
se	[.0271]	[.0489]	[.028]	[.0439]	[.0685]	[.0444]
N	25,220	25,220	25,220	25,220	25,220	25,220
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors are in brackets. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

The impact of new highways on intra-city relocation choices carries an implication for firm dynamics. When location changes are not tracked in the data, the rate of firm exit can be inflated, possibly leading to an underestimation of the reduction in exit observed produced by our treatment. Simultaneously, not tracking location changes could lead to an overestimation of firm entry which could potentially result in an overestimation of firm entry rates in treated locations. Lastly, considering that relocations are often motivated by a desire to be closer to clients and suppliers, it is reasonable to expect that revenue productivity tends to be higher at the new locations.

C Appendix: Model

Figure 18: Residual wage by location

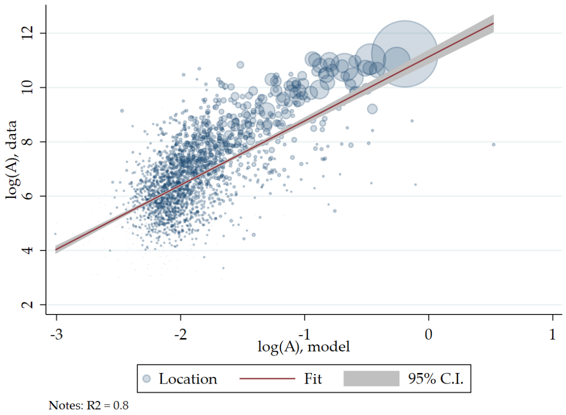


(a) Wage by location, data and residual

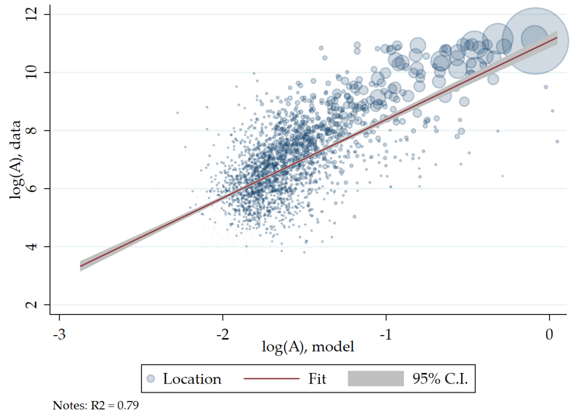
(b) Residual wage/data wage by location

Notes: Figure shows estimation for 2018. Marker size in panel (a) denotes the number of firms; the largest is Mexico City. $\beta_1, \beta_2, \beta_3$ significant at the 95%.

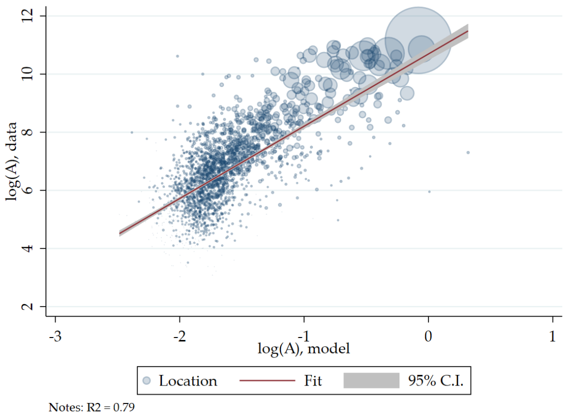
Figure 19: Local labor productivity, model vs. microdata



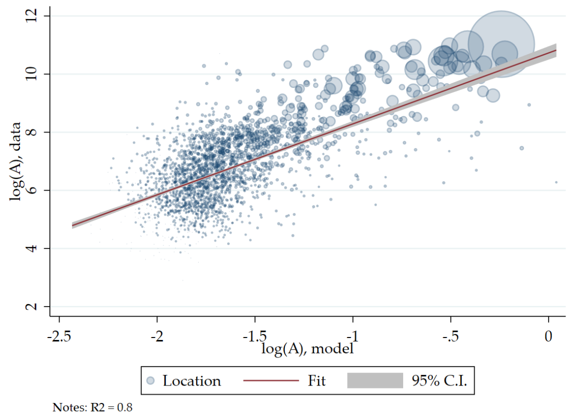
(a) 1998



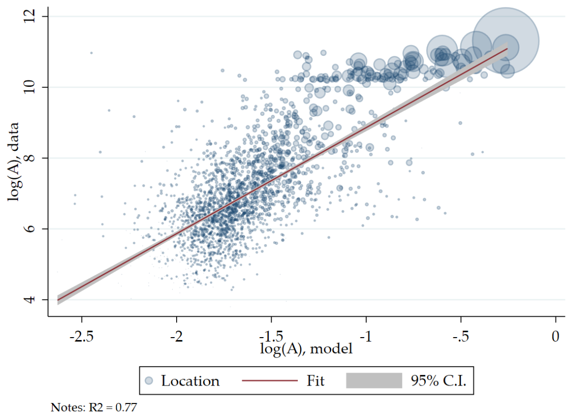
(b) 2003



(c) 2008



(d) 2013

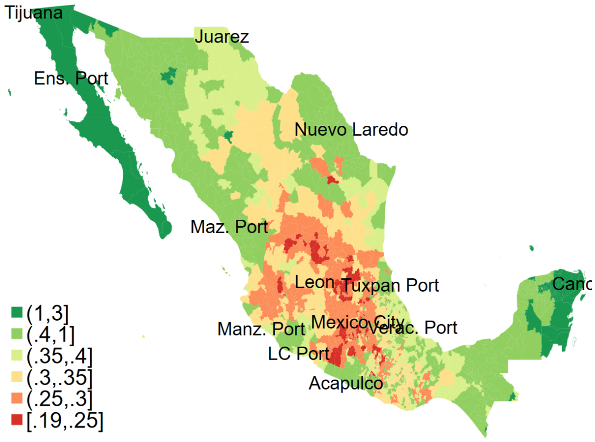


(e) 2018

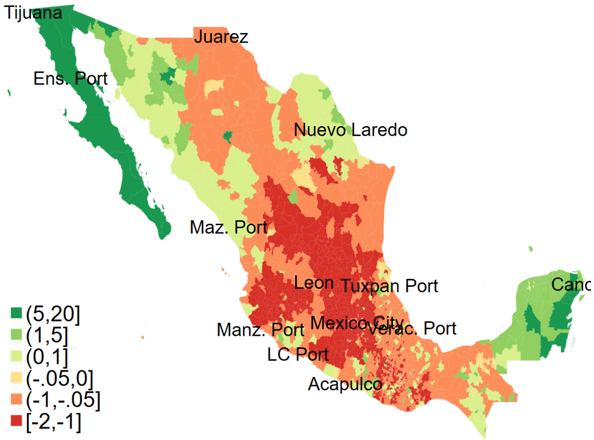
Notes: Gains stemming from expanding the highways network from 1998 to 2018. Gains are at the location level.

Quantitative results

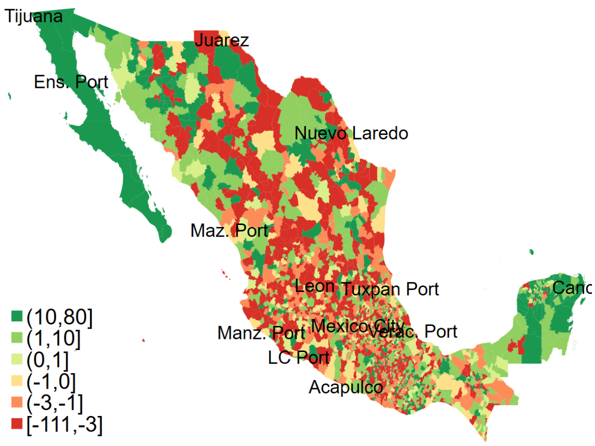
Figure 20: Location gains from the 1998-2018 highways network



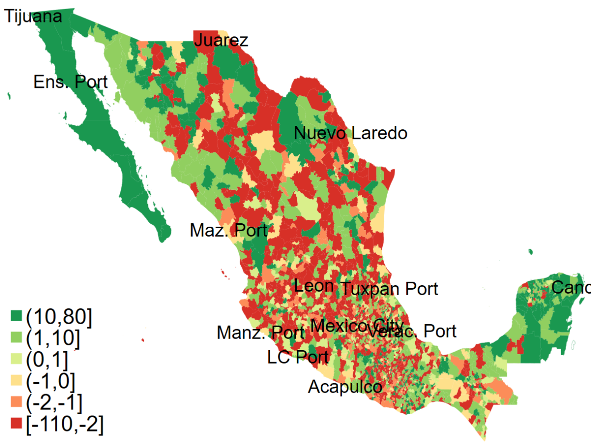
(a) Price index reductions (%)



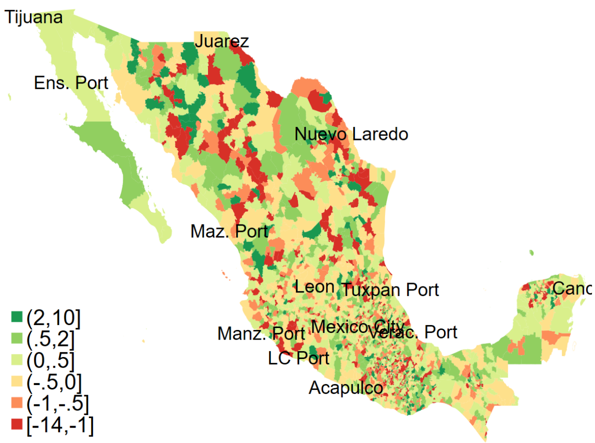
(b) Market access gains (%)



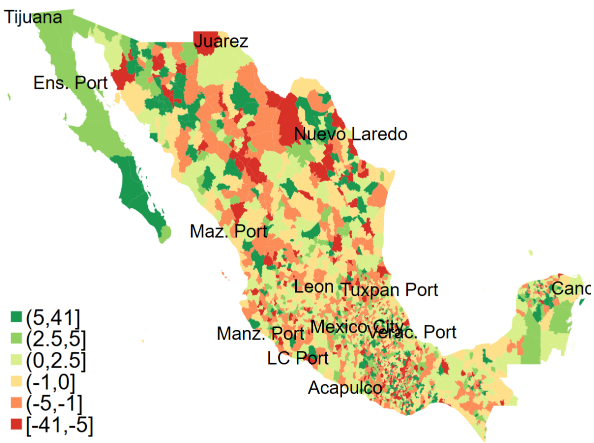
(c) Employment gains (%)



(d) Real revenue gains (%)



(e) Productivity gains (%)



(f) Firms gains (%)

Notes: Gains stemming from expanding the highways network from 1998 to 2018. Gains are at the location level.

Agglomeration externalities

Firm level productivity is separable in two parts as:

$$\psi_{i,t}(n) \equiv z_{i,t} \cdot s_i(n) \tag{49}$$

Now $z_{i,t}$ is not fully exogenous but depends positively on the local population to capture agglomeration externalities stemming from, for example, a larger pool of ideas that make all workers more productive in the location.

$$z_{i,t} = \bar{z}_{i,t} L_{i,t}^{\alpha} {}_{z} \tag{50}$$

Where $\bar{z}_{i,t}$ is the exogenous part and $\alpha_z \geq 0$ governs the degree of agglomeration externalities. The rest of the model remains the same. The existence of the spatial equilibrium will now depend on α_z. Allen and Arkolakis (2014) provide the existence conditions.

Congestion externalities

Utility is still given by:

$$U_{i,t} \equiv C_{i,t} \cdot u_{i,t} \tag{51}$$

But now, local amenities suffer from congestion externalities. The larger the amount of people living in a location, the larger the degradation and congestion of amenities. We can model it as:

$$u_{i,t} = \bar{z}_{i,t} L_{i,t}^{\alpha} {}_{u} \tag{52}$$

Where $\bar{u}_{i,t}$ is the exogenous part and $\alpha_u \geq 0$ governs the degree of congestion externalities. Adding a congestion force reduces the strong negative relationship between local wages and amenities. Allen and Arkolakis (2014) provide the existence conditions of the equilibrium for combinations of parameters governing agglomeration and congestion externalities.