Spatial Misallocation, Informality, and Transit Improvements: Evidence from Mexico City*

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Abstract

Developing countries have failed to enforce taxes across establishments leading to inefficiently high informality. Can transit infrastructure improve input allocation by reducing informality? This paper studies this question in Mexico City. I combine a rich collection of administrative microdata and exploit the construction of new subway lines. Transit improvements reduce informality by seven percent in areas near the new subway stations. I develop a spatial general equilibrium model that accounts for the direct effects of transit infrastructure in purely efficient economies and on allocative efficiency in economies with distortions. Changes in allocative efficiency driven by workers' reallocation to the formal sector amplify the gains by around 25%.

Keywords: Informality, allocative efficiency, urban transit infrastructure.

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1 Introduction

The growth of congestion and commuting times around the world has become a pressing issue for governments and urban planners in developing countries. In Mexico City, it takes a typical low-skilled worker approximately two to three hours to commute to work in the central business district (CBD). In recent decades, governments worldwide have invested heavily in public transportation to alleviate this problem. Recent research examines the aggregate gains from public transit improvements, assuming perfectly efficient economies. However, perfectly competitive models may fail to capture key features of developing economies, where labor market frictions and other economic distortions are salient. In this paper, I study the economic impacts of transit infrastructure, considering the indirect impacts arising from distortions and input misallocation.

The main economic inefficiency I study is informality. Labor market informality is a significant source of distortions in developing countries. Informal firms avoid paying taxes and do not make social security contributions to their workers, generating gaps in the marginal product of labor and other inputs that lower total factor productivity (Hsieh and Klenow, 2009). Specifically, formal firms face higher distortions than informal ones, and as a result, their marginal revenue product of labor (MRPL) is higher relative to informal establishments inducing misallocation. In addition, agglomeration externalities may amplify the inefficiencies in the allocation between the two sectors. The informal sector, typically non-traded services, is less subject to agglomeration effects than the rest of the economy, leading to even more inefficient informality. Thus, the market allocation implies a too-large informal sector relative to the first-best allocation. These intersectoral distortions and differences in agglomeration forces imply that any policy or shock that impacts informality may have first-order effects on welfare through allocative efficiency. In particular, transit improvements may change the extent of informality as the workforce reallocates across jobs within the city.

This research explores how transit improvements impact informality and aggregate efficiency at the city level. I test whether infrastructure projects facilitating transit within a city improve allocative efficiency by reallocating workers from low MRPL (informal) establishments to high MRPL (formal) establishments. If so, the aggregate gains from these projects can be larger relative to those estimated by urban models that assume perfectly efficient economies. The core intuition is that in cities in developing countries, workers in remote locations often prefer to work in low-paid informal jobs near their homes rather than incurring the high commuting cost of formal employment. Transit improvements may thus provide better access to formal jobs, leading to an expansion of the formal sector and a more efficient labor allocation.

The paper makes two main contributions. First, I combine rich administrative microdata with a transit shock to provide new empirical evidence on the relationship between informality and the geography of cities. I estimate the effect of transit improvements on workers' reallocation across the formal and informal sectors. Second, I rationalize these results through the lens of a quantitative spatial model. I extend recent work (Ahlfeldt et al., 2015; Allen et al., 2015; Tsivanidis, 2021) by adding intersectoral distortions, multiple sectors, and factor misallocation to an urban framework. Following Baqaee and Farhi (2020), I provide a formula that decomposes the welfare gains from transit developments into a direct effect present in perfectly efficient economies and a novel allocative efficiency term. This latter term captures two market failures: factor misallocation and differences in external economies of scale across sectors.

I study this question in Mexico City, which is a relevant and informative case study for several reasons. First, it has a dense concentration of economic activity. Second, the informality of the labor force and establishments is typical of developing countries, with over 50% of the urban labor force and 70% of establishments being informal, leading to significant misallocation of resources (Busso et al., 2012; Levy, 2018). Moreover, the city's size and congestion level are similar to other cities in low and middle-income countries such as Bogotá, Sao Paulo, or Río de Janeiro. Lastly, the city constructed a primary subway line in the early 2000s connecting remote areas in the north with the central business district (CBD), offering a unique analysis opportunity.

At the center of the analysis is a rich collection of unique administrative microdata. I observe the geography of jobs and worker residences for both the formal and informal sectors at the census tract level.[1] The paper uses four primary sources of data: i) confidential microdata from the Economic Census, covering the universe of formal and informal business establishments in the city; ii) the Population Census to determine the residence of both formal and informal workers; iii) detailed information on the evolution of the transportation network in Mexico City; and iv) transportation diaries, to construct commuting and trade flows for both the informal and the formal sectors.

The first part of the paper empirically studies the link between the accessibility of jobs and informality. I document two empirical facts in the data exploiting cross-sectional variation. I show that formal jobs concentrate in the city's center and that informal workers are more sensitive to commuting costs. Thus, workers in the outskirts end up working in the informal sector due to poor access to formal employment. I then study the causal impact of new transit on informality.

The main finding suggests that transit improvements reduce informality rates. In particular, I provide causal evidence of this effect by exploiting the opening of a new subway line (line B) that connected remote locations with the center of Mexico City. Specifically, I estimate a series of difference-in-differences specifications that use variation in access to new transit. These specifications control for the initial characteristics of census tracts and capture changes in informality after the transit shock in locations close to the new subway line. The key identification assumption is that the opening dates of these new commuting links were unrelated to other local demand- or supply-side shocks that affected locations near the new line. This assumption is supported by the decades-long planning horizon in which part of the line was included and several unexpected and multi-year delays in the opening schedule due to the 1994 peso crisis. The results imply that the ratio of formal to

[1] This is a unique characteristic of the Mexican data since I can observe directly which establishment is formal or informal. For instance, this differs from other datasets, such as India, where researchers use size as a proxy of informality. Throughout the paper, I use the standard definition of informality: a worker is informal if she does not receive social security benefits based on the contractual relationship with the employer.

informal residents increases by approximately 7%-9% in locations close to the new stations, and workers' informality rates decrease by 2 to 4 percentage points after the opening of the new line.

I also perform two additional exercises to check the robustness of the results. I use an expansion plan from 1980 and compare the new line with similar planned metro lines that were not completed over this period for unrelated reasons. Reassuringly, this robustness check yields similar estimates to the baseline specification. In addition, to solve remaining endogeneity concerns regarding the allocation of infrastructure, I built an instrument based on the Least Cost Path in terms of elevation that connected the main economic centers (Faber, 2014). The idea of the instrument is to capture the routes that planners would have built to minimize costs and connect the main centers. The identification assumption is that the routes based on cost-minimization are unrelated to local shocks. The results are stronger relative to the baseline specification suggesting that the locations that experience the shock due to the cost minimization experience larger decreases in informality.

One remaining concern with identification is a change in the composition of households in areas close to the new stations. To examine this, I conduct three additional exercises to control for the potential sorting of households. First, I find that the transit shock did not lead to changes in the composition of households based on observable characteristics. Second, I also show similar mobility patterns between the treated and control locations using retrospective questions from the population census in which they ask about the previous State of residency. And third, I ran the main specification in two different samples: i) the sample of workers that did not change the State of residence, and ii) I merged the population census by age, gender and block and ran the regression only on this sample finding similar effects. The idea is to compare a group of individuals that were similar at the moment in which the Government opened the new line.

The results imply that transit improvements may generate larger welfare gains than the ones typically emphasized in the literature. I build a quantitative model with multiple sectors and wedges to study this effect. The model allows me to quantify the aggregate effects of new infrastructure, taking into account the impact on factor allocation. I provide a formula in an urban setting that decomposes the welfare effects of any trade/commuting costs shock into two components: a direct effect and a novel allocation term. The allocation term increases welfare if workers reallocate to establishments with higher distortions (higher MRPL) or stronger agglomeration forces. The intuition is that firms with a higher wedge and larger agglomeration forces are too small in the market allocation relative to the first-best.

The key parameters that drive the welfare gains are the labor supply elasticity across sectors, the wedge between the formal and informal sectors, and the size of external economies of scale.

First, I estimate the labor supply elasticity across sectors, which governs the reallocation of workers from the informal to the formal economy. I propose a new strategy exploiting variation across locations after the shock by running a triple-difference estimator that associates changes in labor allocation between the formal and informal sectors with changes in market access.[2] I follow

[2]This empirical strategy based on the model can be very useful for estimating labor supply elasticities across sectors

Tsivanidis (2021), and Donaldson and Hornbeck (2016) and compute market access measures for residents and firms by sector. Intuitively, the market access measures represent a wage index by sector including commuting costs. Suppose a transit shock connects workers to better formal jobs relative to informal jobs. In that case, workers experience an improvement in the wage index of the formal sector relative to the informal one, and they reallocate from the informal to the formal economy. I find that the estimates for the labor supply elasticity parameter, around 2, are consistent with the recent empirical evidence of labor supply elasticities across sectors (Galle et al., 2017).

I use two different approaches to calibrate the wedges that yield similar results. First, I follow Hsieh and Klenow (2009) and Bau and Matray (2020) and use the inverse of the labor and capital shares. Under the assumption that all firms within the same sector use the same production function, differences in these shares capture the wedges corresponding to all types of distortions such as taxes, subsidies, markups, enforcement, and other regulations. Second, I use a more conservative approach following Levy (2018), which documents differences in taxes, subsidies, and other distortions between formal and informal establishments in the Mexican economy. I assume a constant wedge for formal firms considering all the distortions and a zero wedge for informal ones.

Regarding the size of external economies of scale, I find higher agglomeration in the formal sector. In particular, the model implies that trade elasticities capture agglomeration forces due to a love of variety. Then, I recover these parameters by estimating gravity equations relating trade flows to travel times for both sectors. The main finding is that the trade elasticity is lower for the formal sector implying that agglomeration forces are higher for formal establishments.

Armed with these estimates, I quantify and decompose the welfare gains from rolling out the new subway line by varying trade and commuting costs in the GE model. I find that the allocative efficiency margin drives a significant fraction of the total gains. The results suggest that the new subway line increased welfare by around 1.6%. I find that the direct effects explain approximately 78% of the total gains, while the reallocation of workers from informal to formal firms explains 19%, and the remaining 3% are driven by differences in agglomeration between the two sectors.[3] In terms of the cost-benefit analysis, the allocative efficiency margin increases net welfare by 26%. I simulate other policies that the Government can implement to reduce informality, such as decreasing the entry fixed cost for formal firms finding that transit infrastructure that connects informal workers with formal employment can be an effective tool for this purpose. For example, the entry fixed cost has to decrease by more than 10% to reduce informality in a similar magnitude.

Overall, the findings suggest the importance of considering the role of the allocative efficiency margin in the optimal allocation of infrastructure as distortions can change the welfare gains of these projects (Balboni, 2019; Fajgelbaum and Schaal, 2017; Santamaría, 2020).

or occupations in space. For example, Khanna et al. (2022) follows this strategy to estimate an elasticity that governs the choice between criminal gangs and formal jobs in Medellín.

[3]In the analysis, I compute two counterfactuals to control for the potential sorting of households. The first one allows workers to migrate and reallocate across locations within the city. The second one holds constant the population in each census tract. The results of both counterfactuals are very similar.

Related Literature

This paper contributes to different strands of the literature. The first is the economic geography and urban economics literature, which has assessed the economic impacts of urban infrastructure. The second is the macro-development literature, which has studied the main drivers of allocative efficiency and its effect on TFP. This latter strand is related to a large literature on international economics that has estimated the impact of trade shocks on allocative efficiency in the presence of domestic distortions.

First, a new strand of literature has explored the impact of transit infrastructure within cities (Ahlfeldt et al., 2015; Baum-Snow, 2007; Gonzalez-Navarro and Turner, 2018; Heblich et al., 2018; Tsivanidis, 2021). For example, Tsivanidis (2021) assesses the distributional effects of a new bus rapid transit system in Bogotá, and Heblich et al. (2018) study the economic consequences of the subway in London. My paper extends the basic framework and adds multiple sectors and market failures. It shows how to decompose the effect of transit shocks using a first-order approximation in perfectly efficient economies and in an economy with distortions.

The paper also contributes to the literature on the role of factor misallocation in lowering aggregate TFP (Banerjee and Duflo, 2005; Hsieh and Klenow, 2009; Restuccia and Rogerson, 2008). These studies have shown that the dispersion in distortions across establishments generates factor misallocation, more so in developing than advanced economies. In the case of Mexico, Busso et al. (2012) shows that if workers reallocate from the informal to the formal sector by eliminating wedges, TFP increases by 200%.[4] This paper contributes to this literature by analyzing the interaction between city transit infrastructure and input misallocation.

Third, my work also contributes to a strand of the international economics literature that studies the gains from trade through the allocative efficiency channel. This literature was recently reviewed by Atkin and Donaldson (2021); Atkin and Khandelwal (2020), who discuss the role of distortions on the aggregate gains from market integration. Most of these articles have explored the response of markups to trade liberalization episodes or changes in infrastructure (Arkolakis et al., 2019; Asturias et al., 2019; Edmond et al., 2015; Holmes et al., 2014; Hornbeck and Rotemberg, 2019). Similar to my paper, some studies have analyzed the effect of intersectoral distortions on welfare (Święcki, 2017), and the effect of trade on informality (Dix Carneiro et al., 2018; McCaig and Pavcnik, 2018; McMillan and McCaig, 2019). While this literature focuses on trade reforms that affect labor demand, my paper examines the impact of commuting and urban trade on aggregate productivity.

Other studies, such as Moreno-Monroy and Posada (2018) and Suárez et al. (2016), have also explored the relationship between commuting and informality from a theoretical perspective using search models. They argue that the high commuting cost to a formal job faced by a large part of the population increases informality rates in developing countries. My paper investigates this

[4] Other studies have aimed to understand the leading causes of the significant levels of resource misallocation in developing countries. Some primary explanations consist of regulations, markups, and the wedges caused by the informal sector. Similarly, other papers such as Fajgelbaum et al. (2019), and Hsieh and Moretti (2019) have shown that state taxes and housing restrictions generate spatial misallocation in the US.

relationship empirically and quantitatively. First, I provide empirical evidence on the relationship between informality, the spatial structure of cities, and transit infrastructure. And second, the paper is the first to measure the economic impact of infrastructure on allocative efficiency due to informality, a common phenomenon in developing countries.

The rest of the paper is organized as follows. Section 2 introduces the setting of my study in Mexico City and describes the transit shock. Section 3 presents the reduced-form evidence of the effect of commuting on informality. Section 4 develops an urban quantitative model with multiple sectors, intersectoral distortions, and resource misallocation. Section 5 estimates the main parameters of the model. Section 6 quantifies and decomposes the welfare gains from transit improvements and run other counterfactuals. Section 7 concludes.

2 Institutional Context

2.1 Transit System

In the second half of the twentieth century, Mexico City had severe public transport problems, with congested main roads and highways, particularly in the downtown area. In 1967, the Government established a decentralized public office to build and operate a rapid transit system of underground trains to facilitate public transportation in Mexico City. Two years later, on September 4, 1969, the Government inaugurated the first line. Today, the system has grown into 12 lines with 195 stations, for a total length of 128.4 miles. The subway is the largest in Latin America and the second-largest system in North America after the New York City Subway.

The Plan Maestro 1985-2010 guided the expansion of the subway. It set the mobility goals that the transport system needed to satisfy over the long run, based on best practices in urban development and the operational constraints of the project. The Plan Maestro 1985-2010 underwent some modifications from what the Government had initially planned. For example, Line B was originally Line 10 and experienced extensive changes (Ramírez et al., 2017). These modifications responded mainly to changing demand patterns for transportation in Mexico City, which forced the Government to redesign some lines. Part of my empirical strategy is to compare the unplanned modifications to the subway lines with the original and un-executed plans.

In my empirical strategy, I exploit the construction of line B. This line had the distinct feature of connecting informal workers in remote areas with jobs in the central business district (CBD). It was inaugurated in 2000, and most of it was initially planned as part of Plan Maestro 1985, reducing potential endogeneity concerns between the opening of the new stations and local demand/supply shocks. Moreover, the construction of the line also experienced multiple delays, given changes in the regulatory framework and the 1994 financial crisis, suggesting that the opening of the new stations is unrelated to local shocks. For instance, the government's initial plan was to finish the line in 1997. However, they finished the construction of the entire line in 2002. The line is approximately 20 km long and has 21 stations. It connects the city's metropolitan area with some adjacent municipalities in Mexico State, such as Ecatepec de Morelos and Ciudad Nezahualcoyot. These areas are characterized by high poverty rates, low education, and high informality rates. It is the line with the fourth-highest number of passengers in the network. The total cost of this line, including the net present value of service operations, maintenance, and other overheads, was $2,900 million in 2014 USD dollars, which represents 0.7% of the total GDP of the city.

Figure 1 depicts a map of the Mexico City subway system in 2000, highlighting the lines that I use in my empirical strategy. Line B (purple) connects the northeastern area, including locations in the State of Mexico, with the center of the city. I also use line C and line 12 for robustness checks. Line C (green) was planned as a feeder line in the early 2000s, similar to line B; however, the Government never constructed it. Line 12 (red) is the newest subway line in Mexico City and was opened in 2012.

2.2 Informality

Following Busso et al. (2012); Kanbur (2009), and Levy (2018), I use two definitions of informality. The first is the standard definition and is based on whether firms comply with labor regulations. A worker is defined as informal if the firm does not pay social security taxes. Social security benefits include health care, savings for retirement, social benefits for recreation, and invalidity allowances. These workers can be salaried or non-salaried workers. The second definition of informality covers self-employed workers and family members that work in a household business. The latter definition is a more restrictive one, as it includes only the non-salaried workers of the first group.

As in most developing countries, informality in Mexico is a significant problem. It affects 57% of the total workforce and 78% of firms (INEGI). Figure B1 in the Online Appendix compares informality rates (using the standard definition) in countries in Latin America and the Caribbean to the average of the OECD. Informality rates in the entire region are very high. The average across the region is 50%, which is much higher than the OECD average of 17%. Relative to other countries in the region, Mexico has one of the highest informality rates, and the difference is larger when we compare Mexico to other countries with a similar income level, such as Argentina or Colombia.

The presence of the informal sector and the fact that informal firms avoid paying taxes create wedges across establishments. According to recent estimates, a firm that fully complies with salary regulations is expected to pay social security taxes amounting to 18%-33% of a worker's wage (Busso et al., 2012; Levy, 2018) and 20% on sale taxes. These wedges create distortions across firms that decrease welfare and TFP. Figure B2 in the Online Appendix plots the size and productivity distribution of different definitions of formal and informal firms in the Mexican context. Informal firms are smaller and less productive than formal firms. Removing the distortions between the formal and the informal sector would increase TFP in Mexico by around 200% (Busso et al., 2012).

3 Data and Reduced Form Effects

3.1 Data

My primary unit of observation is the urban census tract (Area Geoestadística Básica in the Mexican micro-data). I use a sample of approximately 3,500 census tracts from 116 different neighborhoods and 24 different municipalities.

The first source of information is standard GIS data on the evolution of the transportation network, the new transit subway lines, and data on roads and highways in Mexico City that I use to calculate commuting times.

The second source of data is the Mexican Economic Censuses collected by INEGI. This is a unique establishment dataset that provides information on sales, value added, number of workers, salaried workers, social security, and other outcomes. The census is carried out every five years starting in 1994. A unique characteristics of this dataset is that I can observe informal establishments at a very high granular level.[5] I calibrate wedges for each location and sector using wage bill, sales, and social security payments.[6]

The third source of information is the Mexican Population Census. This census is carried out every ten years, and INEGI has provided the data since 2000. With this information, I can calculate the number of informal, formal, and total residents in each location. The 2000 Population Census also reported other variables, such as household income and job characteristics, that I use in the empirical strategy. I also use the 2015 Intercensal Survey and 2017 Origin-Destination Survey collected in Mexico City to infer trade and commuting flows across the different municipalities in the city.

Section A in the Online Appendix documents two empirical facts in the cross-section that show a negative relationship between the accessibility of jobs and informality. First, formal jobs concentrate more in the center, while informal workers live in the outskirts implying that workers in the periphery have poor access to formal employment. Second, I show that informal workers are more sensitive to commuting costs than their formal counterparts, so they work closer to their homes and do not commute to the CBD. Based on these facts, I now focus on the causal impact of transit infrastructure on informality.

3.2 The Causal Effect of Transit Infrastructure on Informality

The main finding suggests that informality rates decrease with transit improvements that improve market access of formal employment to informal workers. In particular, I exploit the construction of line B of the subway in Mexico City by estimating a series of difference-in-differences specifications.

[5] This is a unique characteristic since most datasets in developing countries only cover formal firms and researchers use as a proxy of informality the size of the firm.

[6] For the Economic Census, I observe data for periods before and after the transit shock, which allows me to test for parallel trends in my main specification.

I compare locations close to the new subway line with locations in the rest of Mexico City and test whether those that improved their market access experienced a change in informality rates after the transit shock while controlling for initial characteristics. One feature of line B is that it connected remote locations in the State of Mexico, close to Ecatepec de Morelos, with the city's center. The identification assumption is that the opening of the new stations is uncorrelated with local demand/supply shocks. The fact that most of the line was planned decades earlier makes this assumption plausible. Moreover, since the construction of infrastructure may be endogenous (Redding and Turner, 2015), I include a set of covariates as controls to compare similar areas and build an instrument based on the least cost path.[7]

I use data from the Population Censuses and estimate the following specification relating the transit shock to the change in the ratio between formal and informal workers:

$$\Delta\left(\ln L_{iF} - \ln L_{iI}\right) = \beta \mathrm{T}_i + \gamma X_i + \delta_{s(i)} + \epsilon_i, \tag{3.1}$$

where L_{is} is the number of individuals that live in census-tract i and sector s, T_i is one of four different treatment variables: log distance in meters, log distance in walking minutes, a dummy variable indicating whether the closest station is within the 10th percentile of the Euclidean distance, and a dummy variable whether the closest station is within 25 minutes, $\delta_{s(i)}$ are state or municipality fixed effects,[8] and X_i is a vector of census-tract characteristics that include distance controls such as: the area in square kilometers, distance to other stations of public transit, a central business district dummy variable, and some productivity measure in the baseline year in which I include value added per worker and the number of firms to capture how good is the location in terms of jobs. This equation relates the transit shock to the log of the ratio between formal and informal workers.[9] I estimate equation 3.1 for the pool of workers and for different groups based on skills.[10]

Table 1 reports the results for different specifications of equation 3.1. Overall, the results imply that locations close to the new subway line experienced a decrease in workers' informality rates. In particular, the ratio of formal to informal individuals increased between 3.0% and 6.9% after the shock. These results are robust to different specifications, for example, to the use of different definitions of the treatment variable or to the use of different sets of fixed effects or controls. In addition, in panels C and D, I control for the change in workers' composition in terms of skills and report the results only for low-skilled workers. The estimates are very similar to the ones found for the entire pool of workers. For instance, the ratio between formal and informal low-skilled workers increased on average between 4.0% and 7.1%. Moreover, in panels E and F, I report the results

[7] Another potential concern to the identification is sorting given by a change in the residents that prefer to work in the formal sector. I show in the next section that household characteristics are not correlated with the opening of line B and similar mobility patterns between the treated and control locations.

[8] For the municipality fixed effects specifications, I classify locations in the State of Mexico into four different groups: northwestern, northeastern, west central, and east central for a total of 20 municipalities.

[9] Equation 3.1 corresponds to a structural relationship that I will derive from the model in section 5.

[10] One caveat of this specification is that I cannot test for parallel trends due to data constraints because I cannot observe the location of informal/formal residents before the 2000 Census.

restricting the sample to the areas not located in the CBD of Mexico City. The effects should be larger in these locations since more informal workers live in these areas. I find larger effects for this specification; the ratio between formal and informal workers increased by almost 10%.

Moreover, in table C4 I estimate line B's effect on the overall log number of individuals and disentangle the effect from the previous regression between formal and informal workers. In panel A, I report the results for the pool of workers, while panels B and C report the results for the number of formal and informal workers. The dependent variable in the first and third columns is the log number of workers. On the one hand, the point estimates suggest that the effect is very small on the number of individuals. For instance, it is only 1.7% in the case of the pool of workers, and 2.2% for low-skilled. On the other hand, the second and fourth columns show the estimates for the log number of formal workers. The results suggest that the locations affected by the shock experienced an increase in formal workers between 3% and 6%.

There are two main potential concerns regarding the interpretation of this effect. First, line B may be endogenous; I address this concern in section 3.2.1 by comparing line B with planned lines and building an instrument based on the least cost path. Second, worker sorting may explain the results. I address this concern in section 3.2.2 by running the same specification for different samples and comparing reallocation decisions between the treated and control areas.

I also use data from the Economic Censuses and test whether the shock also generated an indirect effect affecting the "treated" location in terms of jobs. I estimate a difference-in-difference specification using as a baseline the year 1994.

Figure 2 and table C5 report the point estimates for the main outcome, the share of informal workers. I find that workers' informality rates decrease in locations near line B after the transit shock. I also find evidence of parallel trends since the point estimate is small and not significant in 1999. On average, informality rates decrease between 2.0 and 4.0 percentage points in locations that experienced the shock.

3.2.1 Robustness Checks

Comparison with other lines

For the robustness checks, I compare locations close to line B of the subway with locations near subway expansions that the Government planned to build in the 1980s or actually built years later. In particular, panel b of Figure 1 plots a map of Mexico City highlighting the three lines that I compare: Line B, which is the infrastructure project that I'm studying; line C, a feeder line, similar to line B, that was designed to connect northwestern locations with the center of Mexico City, but was never built; and Line 12, which is the latest subway line, opened in 2012.

I estimate the same difference-in-differences specification from the baseline regression. The only difference is that the treatment variable corresponds to a dummy variable indicating whether the centroid of the census tract is within some buffer zone of line B (i.e., 1500 meters), and the control group consists of locations within some buffer zone of line C and/or line 12. I run these regressions for four different buffers: 1500, 2000, 2500, and 3000 meters.

Figure B6 in the Online Appendix depicts the point estimates for the log of the ratio between formal and informal workers from equation 3.1. I find a similar pattern to the previous results. The log of the ratio between formal and informal workers increases by approximately 10% when I compare treated locations with census tracts close to the other two lines. As shown, in the graph, this finding is robust to the use of different buffer zones and very stable.

In addition, Figure B7 in the Online Appendix depicts point estimates for workers' informality. There is a negative relationship between informality rates and transit improvements. For instance, informality rates for workers decrease on average between 4.0 and 11.0 percentage points.

Least-Cost Path

Since the allocation of the infrastructure can be endogenous, I also build an instrument for line B following the approach from Faber (2014) of the least cost path. Specifically, I built the routes connecting line B's four main stations: Ciudad Azteca, Nezahualcoyotl, San Lazaro, and Buena Vista, and used a dummy variable if the centroid of the census tract is within the 10th percentile. The identification assumption is that the routes based on cost minimization are unrelated to local labor supply and demand shocks.

Table C7 in the appendix presents the results. Overall, I find more substantial effects using this approach. For instance, for the pool of workers, I find that the ratio of formal to informal residents increased by 12%, while in the baseline scenario, this number is only 7%. Similarly, I find that for low-skilled workers and the outskirts areas, the effect is around 19%, while in the baseline scenario, the impacts are only 7% and 10%, respectively. These findings suggest that the locations that improve their market access due to cost minimization experience larger decreases in informality.

3.2.2 Households' Composition and Migration Patterns within the City

A reminder concern regarding the identification strategy is that locations close to the new subway line might experience a change in the composition of households due to worker sorting.[11] For example, high-skilled workers that would prefer to work in the formal sector might migrate to these census tracts and, as a result, there would be a decrease in informality rates that could explain my findings. Ideally, I would deal with this issue by using a multi-year panel of workers before and after the shock. Unfortunately, no such panel is available.

To deal with this concern, I perform different exercises. First, I compare household characteristics before and after the shock. The goal is to show that in terms of observable covariates, there was no change in households' composition, which would imply that most of the census characteristics did

[11]In the model, I am allowing for changes in terms of unobserved characteristics since it allows for migration within the city. However, the model only assumes one type of worker and, therefore, in the empirical section, I analyze changes in households' composition in terms of observed characteristics.

not change except for informality rates. For that purpose, I run the same specification in equation 3.1 on different outcomes of household characteristics. Second, I use retrospective questions to show similar mobility patterns between the treated and control locations. And third, I estimate the main specification in different samples.

Table 2 reports the results, including all the set of controls. On average, I find that household characteristics in locations close to line B were not affected by the shock relative to other areas. For example, the point estimates for the share of high-skilled workers, the number of kids, or the household size are not significant and are precise zeros. One explanation of this result is that historically, these locations have been very poor and dangerous in terms of crime and homicide rates. Then, it is unlikely that people decided to move into these areas even with a new subway line and an improvement in market access since these locations have very low amenities. Overall, in terms of observable characteristics, there is no change in households' composition due to the transit shock that can bias my estimates.[12]

Furthermore, I also show similar mobility patterns between the treated and control locations. In particular, in the population census, INEGI asks about the State where the person lived before. I estimate a linear probability model relating the probability of changing the State of residence vs. the treatment dummy variable and an interaction between this variable and whether the worker was formal in 2010. Since the remote locations that experienced the market access improvement are in the State of Mexico, this variable captures the reallocation of workers from the CBD to the outskirts of the city. I ran this specification at the individual level, including the population controls and with clusters at the census tract level. Table C9 in the Online Appendix reports the point estimate. The findings imply very similar mobility patterns between the treated and control locations. In addition, I do not find differentiated effects between the formal and informal workers in these areas, suggesting that worker sorting is not driving the results on informality rates from the previous section.

Finally, I ran two alternative specifications changing the sample to show that sorting does not drive the results. First, I merge the population census at the block level by age and gender for those individuals between 12 and 65 years old in both periods. The idea is to compare similar individuals over time. Second, I restrict the sample to the individuals that did not change their State of residency for the new population census. Since the treated locations are in Mexico State, this is a good proxy to control for sorting from Mexico City in which the CBD is located. Table C8 in the online appendix reports the results. The first four columns report the results for the first sample. and the remaining four columns for the sample that did not change the State in which they were living before.

I find that for the sample that I crossed by age, block and gender the effect is a bit lower but still

[12]This result corroborates the findings of other papers in the Mexican and Latin American context. For example, Gonzalez-Navarro and Quintana-Domeque (2016) exploit a random allocation of street asphalting in peripheral neighborhoods in Veracruz. The authors follow individuals for two years and find a negligible reallocation of households across locations in the city. Similarly, Hernández-Cortés et al. (2021) find negligible reallocation effects exploiting subways and BRT expansions in Mexico City, and Warnes (2021) shows that the BRT in Buenos Aires did not change residential patterns between low and high-skilled workers.

significant, while in the case, in which I restrict the sample for the population that did not change the State in which they were living, the point estimates are very similar to the baseline specification. For example, for the pool of workers the effect is around 6% and for the outskirt areas the point estimate is 10%.

4 Model

In this section, I present a quantitative model to assess first-order aggregate welfare effects of transit infrastructure on allocation. The model is built on recent work by Tsivanidis (2021), Monte et al. (2018), Heblich et al. (2018), and Ahlfeldt et al. (2015). I extend the basic framework by adding multiple sectors, intersectoral wedges, resource misallocation, and differences in consumption across locations.

The main theoretical result is a formula hat decomposes the total change in welfare into two different components: the first term is a "direct" effect term, and the second one is an allocation term that captures market failures. This latter term can also be decomposed into a resource misallocation term and an agglomeration externality term.[13] [14]

In the model, I assume that there are three groups of agents: workers denoted by L, house owners denoted by H, and commercial floor space owners denoted by Z.[15]

4.1 Preferences

There is a mass of $\mathcal{N}$ locations that are indexed by n and i. There is a mass of L_L workers that operate in 2 sectors indexed by $s \in I, F$, where I and F represent the informal and formal sectors respectively. The utility function takes a standard Cobb-Douglass form. Consumers obtain utility from a composite consumption good and housing. The utility function of worker ω is:

$$U_{nis\omega} = \left(\frac{C_{nis\omega}}{\alpha}\right)^{\alpha} \left(\frac{H_{nis\omega}}{1-\alpha}\right)^{1-\alpha} \cdot d_{nis}^{-1} \cdot \epsilon_{nis\omega},$$

where C is consumption, H is housing, the parameter α is the expenditure share on the consumption good, d_{nis} is an iceberg commuting cost to move from location n to i specific to each sector, and ϵ is an idiosyncratic shock to worker ω. After solving the maximization problem, the indirect utility of worker ω living in location n and working in sector s and location i is

[13] I called the second term an allocation term since both the resource misallocation component and the agglomeration externality term correspond to market failures.

[14] This formula is similar to the general case from Baqaee and Farhi (2020) of GE models on changes in productivity. For instance, in the case of Baqaee and Farhi (2020) all the reallocation effects come from input wedges, while in this model there are two sources of market failures input wedges and external economies of scale.

[15] The focus of the paper is efficiency. In the Appendix, I generalize the results to consider different group of workers such as high- and low-skilled workers. Intuitively, the results are isomorphic if preferences for the formal and informal sector come from the scale parameters of Fréchet shocks, or if the commuting and labor supply elasticities differ between the two groups, and low-skilled workers prefer to work in the informal sector. Given that the subway benefit more low-skilled workers, we can interpret the results in the counterfactual as lower-bound effects.

$$V_{nis\omega} = \frac{w_{is} d_{nis}^{-1} \epsilon_{nis\omega} (1+\bar{t})}{P_n^{\alpha} r_n^{1-\alpha}}, \tag{4.1}$$

where w_{is} is the wage per efficiency unit in location i, and sector s, P_n is the price index of the consumption good, r_n is the rent for housing, and $\bar{t}$ is a proportional tax rebate from the Government. In the Online Appendix, I show the results when the rebate is only given to formal workers. The term $\epsilon_{nis\omega}$ is an idiosyncratic utility shock that is drawn from a nested Fréchet or extreme-value type II distribution $H(\cdot)$,

$$H(\vec{\epsilon}) = \exp\left[-\sum_n B_n \left(\sum_s B_{ns} \left(\sum_i \epsilon_{nis}^{-\theta_s} \right)^{\frac{\kappa}{\theta_s}} \right)^{\frac{\eta}{\kappa}} \right], \text{ with } \eta < \kappa < \theta_s \quad \forall s.$$

Each worker receives a one-time shock and makes three decisions, one for each nest: 1) location to live, 2) sector (formal or informal), and 3) workplace.[16]. In the Online Appendix, I derive the model when the shock is to efficiency units instead of utility units. The parameters η, κ, and θ_s measure productivity dispersion across locations, sectors, and workplaces respectively and capture the notion of comparative advantage.[17] On the other hand, the parameters B_n capture specific amenities that attract residents to each location n. I assume that these parameters are fixed over time.

I allow the third parameter θ_s to differ across sectors to capture the fact that productivity differences across locations are larger in the formal sector, or in other words, that formal jobs are more difficult to substitute across locations than informal ones. This parameter also represents the commuting elasticity. The estimation $\theta_F < \theta_I$ implies that informal workers prefer to work close to their residence, as documented in Section 3.

From the properties of the Fréchet distribution, the probability of living in location n and working in (i, s) is

$$\lambda_{nisL} = \underbrace{\left(\frac{B_n P_n^{-\alpha\eta} r_n^{-(1-\alpha)\eta} W_n^{\eta}}{\sum_{n'} B_{n'} P_{n'}^{-\alpha\eta} r_{n'}^{-(1-\alpha)\eta} W_{n'}^{\eta}} \right)}_{\lambda_{nL}} \underbrace{\left(\frac{B_{ns} W_{ns|n}^{\kappa}}{\sum_{s'} B_{ns'} W_{ns'|n}^{\kappa}} \right)}_{\lambda_{nsL|n}} \underbrace{\left(\frac{w_{is}^{\theta_s} d_{nis}^{-\theta_s}}{\sum_{i'} w_{i's}^{\theta_s} d_{nis'}^{-\theta_s}} \right)}_{\lambda_{nisL|ns}}, \tag{4.2}$$

where $W_n^{\kappa} = \sum_{s'} W_{ns'|n}^{\kappa}$ is a wage index from location n, and $W_{ns|n}^{\theta_s} = \sum_{i'} w_{is}^{\theta_s} d_{nis}^{-\theta_s}$ is a wage index from location n and sector s. This probability can be decomposed into three terms as in Monte et al. (2018). First, there is the probability of living in n; second, the probability of working in s

[16] I am assuming that the idiosyncratic shock is to utility, but another possibility is to assume that the shock is to earnings. From a welfare point of view this assumption does not have any implications. In the Appendix, I consider a version of the model with Fréchet shocks to earnings and efficiency units.

[17] Different articles have assumed a similar structure to analyze the allocation of workers across sectors. For example, Lagakos and Waugh (2013) study selection in the agricultural sector in developing countries using this kind of shock; Hsieh et al. (2019) study the allocation of talent in the past 50 years across different occupations in the US, and Galle et al. (2017) study the distributional implications of trade given that workers have idiosyncratic productivities for sectors.

conditional on living in n; and third, the probability of working in i conditional on living in n and operating in sector s. Note that $\sum_i \lambda_{nis|ns} = 1$, $\sum_s \lambda_{ns|n} = 1$, and $\sum_n \lambda_n = 1$.

By the properties of the Frechet distribution, I equate the expected ex-ante utility to a constant:

$$\bar{U}_L \equiv \mathrm{E}[\max U_{nis}\epsilon_{nis}] = \left(\sum_{n'} B_{n'} P_{n'}^{-\alpha\eta} r_{n'}^{-(1-\alpha)\eta} W_{n'}^{\eta}\right)^{\frac{1}{\eta}} \gamma_\eta, \tag{4.3}$$

where γ_η is a constant term.[18] The total amount of labor $\tilde{L}_{is}$ hired by (i,s) is equal to the amount supplied by all locations and is given by

$$\tilde{L}_{is} = \sum_n \lambda_{nis} \cdot \bar{L}_L. \tag{4.4}$$

Thus, the average income in n is $\bar{y}_n \equiv \sum_{i,s} \lambda_{nis} w_{is}$.

4.2 Production of the Composite Good

Preferences for the composite good take a standard CES form of different varieties x across sectors and locations.[19] It is described by a two-nested CES structure. In the first nest, consumers choose between sectors, and in the second nest, they choose between varieties j:[20]

$$C_n = \left(\sum_s C_{ns}^{\frac{\xi-1}{\xi}}\right)^{\frac{\xi}{\xi-1}}, \quad C_{ns} = \left(\sum_i \int_j x_{nisj}^{\frac{\sigma_s-1}{\sigma_s}} dj\right)^{\frac{\sigma_s}{\sigma_s-1}},$$

where the parameter ξ captures the elasticity of substitution across sectors and the parameters σ_s capture the elasticity of substitution across varieties within sectors. Note that the lower nest parameter varies across sectors In principle, we should expect $\sigma_F < \sigma_I$, which implies that agglomeration externalities are larger in the formal sector. I estimate these parameters in the next section by estimating gravity equations. The price index P_n in location n, and the price indices for each sector P_{ns} take the CES functional form:

$$P_n = \left(\sum_s P_{ns}^{1-\xi}\right)^{\frac{1}{1-\xi}}, \quad P_{ns} = \left(\sum_i \int_j p_{nisj}^{1-\sigma_s} dj\right)^{\frac{1}{1-\sigma_s}}, \tag{4.5}$$

where p_{nisj} is the price charged by firm j in (i,s) to consumers in n.

I model the production of each good and the market structure as in the new economic geography

[18] The term $\gamma_\eta = \Gamma(1-1/\eta)$ and $\Gamma(\cdot)$ is the gamma function. This is the usual constant that arises after integrating the pdf from the Fréchet distribution.

[19] Recent work on the public finance literature has shown that consumers, especially on the lower-income levels have preferences for varieties in the informal sector (Bachas et al., 2020).

[20] The CES preferences can be micro-founded using extreme value-type distributions as in the literature that has studied the demand of heterogeneous consumers for a set of differentiated goods (Anderson and de Palma, 1992). For example, Miyauchi et al. (2020) uses this procedure.

literature (Helpman, 1995; Krugman, 1991). Firms compete monopolistically. To produce a variety a firm must incur both a constant variable cost and a fixed cost. Both costs use labor and commercial floor space with the same factor intensity across firms, which implies that the production function is homothetic. The variable cost varies with the productivity from location i and sector s, and it is represented by A_{is}. The total cost of producing x_{ij} units of variety j in location i and sector s is:

$$\Gamma_{isj} = \left(F_s + \frac{x_{isj}}{A_{is}}\right)(w_{is}[1 + t_{isL}])^{\beta_s}(q_i[1 + t_{isZ}])^{1-\beta_s}, \tag{4.6}$$

where w_{is} is the wage per efficiency unit in (i, s), q_i is the price of commercial floor space, and F_s is a fixed cost that varies by sector to capture that the number of firms in the informal sector is larger. In the case of commercial floor space, both sectors face the same price. Finally, I add exogenous wedges represented by t_{isL} and t_{isZ}. These parameters represent taxes and subsidies in each sector and location (i.e., payroll taxes), and they imply that the marginal revenue of labor is not equalized across firms deviating from the optimum. Informal firms avoid paying these taxes, first generating dispersion in TFPR and then lowering TFP.[21] I model informality in a different way relative to recent papers such as Ulyssea (2018) and Dix Carneiro et al. (2018).[22] However, it captures the main differences between the formal and informal economy. First, differences in TFP captured by the parameter A_{is} and differences in the input intensity captured by β_s.

Profit maximization implies that the equilibrium price is the standard constant mark-up over marginal cost. Firms also face iceberg trade costs τ_{nis} to sell goods. In the quantitative analysis, I assume that these trade costs also change after the transit shock. The price charged by firms in i to location n is

$$p_{nisj} = \left(\frac{\sigma_s}{\sigma_s - 1}\right)\frac{\tau_{nis}(w_{is}[1 + t_{isL}])^{\beta_s}(q_i[1 + t_{isZ}])^{1-\beta_s}}{A_{is}}. \tag{4.7}$$

The zero-profit condition implies that the equilibrium output of each variety is constant across firms that operate in the same cell and is given by

$$x_{isj} = \bar{x}_{is} = A_{is}F_s(\sigma_s - 1). \tag{4.8}$$

Aggregate payments to labor and commercial floor space, including taxes, are constant shares of the total revenue in location i and sector s. These shares are captured by β_s and $1 - \beta_s$ respectively:[23]

$$w_{is}(1 + t_{isL})\tilde{L}_{is} = \beta_s Y_{is}, \quad q_i(1 + t_{isZ})\tilde{Z}_{is} = (1 - \beta_s)Y_{is}. \tag{4.9}$$

[21] It is simple to enodgenize these distortions assuming that they are a function of the size in each cell.

[22] In section E.4 of the Online Appendix, I consider a version of the model in which firms endogenously decide to operate in the formal vs. informal sectors following the logic from these studies. Moreover, firms also determine the location to operate in the city.

[23] Total revenue $Y_{is} = \sum_n \alpha\pi_{ns}\pi_{ni|s}X_n$, where X_n is the expenditure from location n.

4.2.1 Expenditure Shares

The assumption of CES preferences implies a standard gravity relationship for bilateral trade flows across locations for each sector. Using the CES demand, the price indices from equation 4.5, and the fact that all firms from (i, s) charge the same price, the share of location n's expenditure on goods produced in (i, s) is:

$$\pi_{nis} = \underbrace{\frac{P_{ns}^{1-\xi}}{\sum_{s'} P_{ns'}^{1-\xi}}}_{\pi_{ns}} \cdot \underbrace{\frac{M_{is} p_{nis}^{1-\sigma}}{\sum_{i'} M_{i's} p_{ni's}^{1-\sigma}}}_{\pi_{nis|s}}, \quad \text{with} \quad P_{ns} = \left(\sum_{i} M_{is} p_{nis}^{1-\sigma_s} \right)^{\frac{1}{1-\sigma_s}}, \tag{4.10}$$

where M_{is} is the total number of firms in location i and sector s, π_{ns} is the share of expenditure in goods from sector s, and $\pi_{nis|s}$ is the expenditure share on goods from i conditional on consuming goods from sector s. Since all firms within the same location and sector choose the same amount of labor and commercial floor space units, the total number of firms is a function of the aggregate amount of labor and commercial floor space:[24]

$$M_{is} = \frac{\tilde{\beta}_s \tilde{L}_{is}^{\beta_s} \tilde{Z}_{is}^{1-\beta_s}}{\sigma_s F_s}, \tag{4.11}$$

where $\tilde{\beta}_s$ is a constant term that varies by sector. The fact that consumers have a love of variety (LOV) and that there is free-entry imply that there are agglomeration externalities. These agglomeration externalisties are captured by the elasticity $\frac{1}{\sigma_s - 1}$. Since the elasticity within the second nest varies by sector, agglomeration externalities generate an additional first-order effect.

4.3 Housing and Commercial Floor Space

I assume that there are two additional industries: $\tilde{H}$, and $\tilde{Z}$ that produce residential housing and commercial floor space respectively. Both of these sectors are non-tradable goods and operate under perfect competition in all locations. The only factors of production of these sectors are the group of agents H, and Z and there is no commuting. The former supplies units to residential housing, and the latter to commercial floor space. The production function for both sectors is linear in labor. Hence, the supply of residential and commercial floor space is perfectly inelastic and is fixed and the prices are given by r_i, and q_i respectively.

Using equation 4.9, the equilibrium condition for the commercial floor space market is:

$$q_i \tilde{Z}_i = \sum_{s} \frac{(1-\beta_s)(1+t_{isL}) w_{is} \tilde{L}_{is}}{\beta_s (1+t_{isZ})}. \tag{4.12}$$

This equation equates the supply of commercial floor space described by the left-hand side to the de-

[24]This model is akin to the perfectly competitive case in which there is a single firm in all locations and sectors, there is perfect competition and there are agglomeration externalities for each sector and location described by $A_{is} = \tilde{A}_{is} \cdot \tilde{L}_{is}^{\beta\gamma_s} \tilde{Z}_{is}^{(1-\beta)\gamma_s}$, where $\gamma_s = \frac{1}{\sigma_s - 1}$.

mand by firms described by the right-hand side. The residential floorspace market clearing condition is:

$$r_n \tilde{H}_n = (1-\alpha) X_n, \tag{4.13}$$

where X_n is total expenditure from location n.

4.4 Government Budget Constraint

The Government collects taxes and gives a rebate to households captured by $\bar{t}$. I assume that the rebate is proportional to household income instead of a lump-sum so that the Government does not distort migration decisions. This rebate is given by the following expression:

$$\sum_{i,s} \left(t_{isL} w_{is} \tilde{L}_{is} + t_{isZ} q_i \tilde{Z}_{is} \right) = \bar{t} \cdot \sum_n X_n. \tag{4.14}$$

This equation implies that the income of the government from the left-hand side is equal to its total expenditure.

4.5 Goods and Labor Market Clearing

I now derive the equilibrium conditions for the goods market-clearing conditions. I analyze the expression first for total expenditure from location n, and then, for total revenue from (i,s).

From equation 4.4, the total labor income received by agents of type $g \in \{L, H, Z\}$ in location n is $\sum_{i,s} w_{is} \tilde{L}_{nisg}$. Then, taking into account the proportional rebate from the government to households, total expenditure from location n is:

$$X_n = \left(\bar{y}_n L_n + q_n Z_n + r_n H_n \right) (1 + \bar{t}). \tag{4.15}$$

On the other hand, the labor demand comes from consumer preferences and the production function. By the properties of the CES preferences, total revenue of location i and sector s, Y_{is}, and the total wage bill $w_{is} L_{is}$ are:

$$Y_{is} = \alpha \sum_n \pi_{nis} X_n, \tag{4.16}$$

$$w_{is} (1 + t_{isL}) \tilde{L}_{is} = \beta Y_{is}. \tag{4.17}$$

This equilibrium condition implies that total payments to workers including taxes is equal to a fraction β of total revenue, where total revenue is a function of expenditures from all locations. Note that taxes t_{isL}, t_{isZ}, and the proportional rebate $\bar{t}$ create trade imbalances since aggregate expenditure is no longer equal to aggregate income in each location n.

4.6 Equilibrium

The general equilibrium of the model is described by the following vector of endogenous variables:

$$x = \{w_{is}, q_i, r_n, \bar{y}_n, W_{ns}, P_{is}, \tilde{L}_{is}, \tilde{Z}_{is}, L_n\},$$

and a constant $\bar{U}$ given a set of exogenous parameters:

$$A = \{d_{ni}, \tau_{ni}, A_{is}, B_n, \bar{L}, \bar{L}_H, \bar{L}_Z, \tilde{Z}_i, \tilde{H}_i, t_{isL}, t_{isZ}, F_s, \theta_s, \kappa, \eta, \sigma_s, \xi, \alpha, \beta_s\},$$

that solve the following system of equations: workplace and sector choice probabilities from equation 4.2; residence choice probabilities from equation 4.2; price indices from equations 4.5 and 4.7; total expenditure from equation 4.15; goods market clearing described by equation 4.17; commercial floor space market clearing described by equation 4.12; housing market clearing described by equation 4.13; labor market clearing; and the Government budget constraint from equation 4.14.

To assure that the equilibrium is unique, I assume the standard conditions for uniqueness in this class of GE models (Allen et al., 2015). Agglomeration externalities need to be lower than congestion forces.[25]

4.7 Welfare Decomposition

To aggregate welfare at the city level, I assume a social planner that takes a utilitarian perspective. The aggregate welfare function is:

$$\bar{U} = \left(\omega_L \bar{U}_L + \omega_H \bar{U}_H + \omega_S \bar{U}_S\right), \tag{4.18}$$

where ω_g represents the weights that replicate the efficient allocation of the economy.[26] This equation suggests that aggregate welfare is a weighted average of the ex-ante utility of the three different agents.

Let's define $\mathcal{L}$ as an allocation of factors of production given a set of exogenous parameters A. Specify $\mathcal{U}(A, \mathcal{L})$ as the welfare function $\bar{U}$ achieved by the allocation $\mathcal{L}$. By a first-order approximation, the total change in welfare of any trade/commuting shock is:

$$d\ln\bar{U} = \underbrace{\frac{\partial \ln \bar{\mathcal{U}}}{\partial \ln A} d\ln A}_{\text{“Direct” effect}} \quad + \quad \underbrace{\frac{\partial \ln \bar{\mathcal{U}}}{\partial L} dL}_{\text{Allocation/Agglomeration}} \quad . \tag{4.19}$$

Equation 4.19 suggests that the effect of any shock can be decomposed into two different terms: a direct effect term that considers just changes in exogenous parameters as iceberg commuting costs

[25] The parametric condition is $(1-\beta_s) + \frac{1}{\eta} > \frac{1}{\sigma_s - 1} \ \ \forall s$.

[26] For the parametric case of my model, these weights solve the following expressions: $\frac{\omega_L \bar{U}_L}{\bar{U}} = \alpha\beta$, $\frac{\omega_Z \bar{U}_Z}{\bar{U}} = \alpha(1-\beta)$, and $\frac{\omega_H \bar{U}_H}{\bar{U}} = (1-\alpha)$.

d_{ni} or trade costs τ_{ni}, and a first-order allocation term. This second term captures allocation from two market failures: wedges and differences in agglomeration externalities between the two sectors.[27]

Under the assumptions of the model, the explicit solution for this expression is:

$$\text{“Direct” effect} = -\alpha\beta \sum_{n,i,s} \lambda_{nisL} \cdot d\ln d_{ni} - \alpha \sum_{n,i,s} \left(\beta_s \lambda_{nL} + (1-\beta_s)\lambda_{nZ}\right) \pi_{nis} \cdot d\ln \tau_{ni} \tag{4.20a}$$

$$\text{Allocation} = \alpha \left(\beta_s \sum_{n,i,s} \left(\frac{t_{isL} - \bar{t}}{1+\bar{t}} \right) \lambda_{nisL} \cdot d\ln \tilde{L}_{nis} + (1-\beta_s) \sum_{n,s} \left(\frac{t_{nsZ} - \bar{t}}{1+\bar{t}} \right) \lambda_{nsZ} \cdot d\ln \tilde{Z}_{ns} \right) \tag{4.20b}$$

$$\text{Agglomeration} = \sum_{i,s} \frac{\beta_s}{\sigma_s - 1} \left(\frac{1+t_{isL}}{1+\bar{t}} \right) d\tilde{L}_{is} + \sum_{i,s} \frac{(1-\beta_s)}{\sigma_s - 1} \left(\frac{1+t_{isZ}}{1+\bar{t}} \right) d\tilde{Z}_{is}. \tag{4.20c}$$

The first term corresponds to a Hulten (1978) or “direct” effect term that comes from an envelope argument. It suggests that under the case of perfectly efficient economies, the cost time-saving approach captures the welfare effect of any trade/commuting shock. For instance, to measure the welfare gains from a transit improvement, it is sufficient to know the value of jobs in each link between n and i since all nominal effects cancel out.[28] This is the cost time-saving formula used by Train and McFadden (1978) to evaluate reductions in commuting costs.

The second term captures changes in allocative efficiency. It suggests that if workers reallocate to sectors and locations with higher wedges, there is an increase in welfare. Hence, a transit shock may have an additional first-order impact in the presence of distortions. Intuitively, the sign depends on whether workers reallocate to firms with larger wedges. Firms that pay higher taxes and face larger distortions have higher values of TFPR, while firms that do not pay taxes have very low values. Thus, if workers move to the firms with higher TFPR, the dispersion of TFPR decreases and the new equilibrium gets closer to the first-best allocation.

Finally, the last term represents agglomeration externalities. This component arises only in the presence of externalities that differ between the two sectors as in BCDR or trade imbalances as in FG. The intuition for this result, is that in a world with trade balances and the same agglomeration force, the productivity gain of one location is offset by the productivity loss in the other location.[29] This latter term captures the effect of these externalities on aggregate TFP and welfare. In the model, agglomeration externalities differ between the two sectors, and wedges and transfers create trade imbalances, so there is an additional effect due to agglomeration. This component depends on two margins: differences in agglomeration externalities, and the wedge. Intuitively, if workers reallocate to the sector with bigger externalities, there are larger increases in welfare. For the wedge, the argument is similar to the second term. Firms that are paying higher taxes are small relative to

[27] This formula applies in the general class of urban models for any wedge, such as, variable market power across firms in product or labor markets. In the Appendix, I show this result.

[28] In his seminal work, Hulten (1978) considers productivity shocks and shows that to measure their effect on GDP, it is sufficient to know the share of sector s on value added, or the so-called Domar weights.

[29] For instance, if agglomeration forces are the same and there are trade balances, we get: $\sum_{i,s} \frac{1-\beta}{\sigma-1} dL_{is} = \frac{1-\beta}{\sigma-1} \sum_{i,s} dL_{is}$, and given the labor market clearing condition, we obtain $\sum_{dL_{is}} = 0$.

the first-best due to trade imbalances; hence, reallocating workers to these firms increases welfare.

I show the derivation of this formula in Section E.1 of the Appendix. I also generalized this result for different groups of workers and a general utility and production function by solving the social planner problem in Section E.2. The only assumptions for this derivation is that the primitive functions of the model are homogeneous of degree one.

Most of the literature whose primarily goal is to measure the welfare gains from transit infrastructure within cities has focused on the first term and direct effects, by assuming that the economy is perfectly efficient. This paper analyzes the effect on the second and third margins.[30]

5 Empirical Strategy and Estimation

In this section, I describe the main empirical strategy and estimation of the main parameters.

5.1 Trade and Commuting Costs

For the counterfactual analysis, I parametrize commuting costs as in the urban economics literature (Ahfeldt et al., 2016). I assume that both iceberg commuting and trade costs are specific to each sector using the following expressions:

$$d_{nis} = \exp(\delta_{ds}\text{time}_{ni}), \tag{5.1a}$$

$$\tau_{ni} = \exp(\delta_{\tau s}\text{time}_{ni}), \tag{5.1b}$$

where time_{ni} is the average travel time in minutes across different transportation modes of moving from location n to location i.[31] The main objects of interest are the parameters δ_{ds}, and $\delta_{\tau s}$ that transform travel times to iceberg costs. I estimate these parameters from a nested logit specification using the 2017 Origin-Destination Survey specific to each sector. I use trips to from home to work and vice-versa to estimate δ_{ds}, and trips to restaurants, outlets, and retail shops to obtain the parameter $\delta_{\tau s}$. Section D in the online appendix provides the details of this estimation.

Table C10 shows the main result after estimating the nested logit specification for each sector. The first two columns report the results for commuting, and the other two columns report the results for trade trips. I obtain a value for δ_{dF} of -0.0090 and for δ_{dI} of -0.0082, which implies that they are very similar. This finding is consistent with the literature (Ahlfeldt et al., 2015). The point estimate for $\delta_{\tau F}$ is -0.0110 and for $\delta_{\tau I}$ -0.0114.

[30]Since this formula applies to the case in which the change in commuting/trade costs is infinitesimal, for the counterfactual analysis, I estimate and decompose the change in welfare using exact hat algebra.

[31]I calculated a weighted average of travel times across the different transportation modes using each transportation mode's aggregate share for commuting and consumption from the travel survey data. Hence, in terms of workers' utility, the assumption is that transportation modes' preferences take a Cobb-Douglas form. This is a conservative assumption. For example, in the case of CES or random idiosyncratic shocks, workers will substitute more other modes of transportation for the subway after the transit shock leading to larger welfare gains.

5.2 Commuting and Trade Elasticities

To estimate the commuting and trade elasticities, I use the 2015 Intercensal Survey and the 2017 Origin-Destination survey. In both surveys, workers report the municipality of their residence and workplace or consumption site. For commuting, I can observe formal and informal workers based on social security information and for consumption, I can observe trips to restaurants, retail shops, and factory-outlets.[32] From the model, I derive the following gravity equations relating commuting flows and trade flows across municipalities and iceberg costs:

$$\ln \lambda_{nism|nsm} = \underbrace{\beta_s}_{\delta_d \cdot \theta_s} \cdot \text{time}_{nim} + \gamma_{ism} + \gamma_{nsm} + \epsilon_{nism}, \tag{5.2}$$

$$\ln \pi_{nism|sm} = \underbrace{\beta_s}_{\delta_{\tau s} \cdot (\sigma_s - 1)} \cdot \text{time}_{nim} + \gamma_{ism} + \gamma_{nsm} + \epsilon_{nism}, \tag{5.3}$$

where the subindex m corresponds to one of four different transportation modes: car, metro or metrobus, bus, and walking; $\lambda_{nism|ns}$ and $\pi_{nism|sm}$ is the share of workers/consumers that commute to location i from location n in sector s using the transportation mode m; time_{nim} is the average commuting time across municipalities n, i using m; γ_{nsm} are origin-transportation-sector fixed effects; γ_{ism} are destination-transportation-sector fixed effects, and ϵ_{nism} captures measurement error.

The goal is to recover the parameters θ_s and σ_s after knowing β_s, δ_{ds}, and $\delta_{\tau s}$ described in the previous section. The parameter θ_s captures how sensitive workers are to commute in the formal/informal sector and σ_s corresponds to the trade elasticity. From the evidence in Section 3, the expected result is that $\theta_I > \theta_F$ and $\sigma_I > \sigma_F$, suggesting that informal jobs and goods are easier to subsitute across locations. Also, the trade elasticity captures agglomeration. I estimate this equation via the Poisson regression by pseudo maximum likelihood (PPML) to include the zero commuting flows between municipalities. Given the set of fixed effects, the identification comes from comparing the decision of workers or consumers that use the same transportation mode and live (work) in the same municipality and sector, but work (live) in different places.

Panel A in Table 3 reports the results for the commuting elasticites. I find a negative relationship between commuting flows and the average commuting times. The commuting elasticity in the formal sector is 3.11, and in the informal sector it is approximately 4.66. These values are consistent with the theoretical assumptions, and they confirm that informal jobs are easier to substitute across locations. Panel B reports the results for the trade elasticity. Trade flows decrease with commuting times. The estimate of σ_s is consistent with the results of previous literature. The elasticity of substitution in the informal sector is 6.94, and in the formal sector it is 5.39, suggesting that agglomeration externalities are larger in the formal sector.

[32] To estimate a different trade elasticity for the informal and formal sectors, I use the fact that most informal establishments in Mexico correspond to restaurants and retail shops, while most formal establishments are manufacturers, as Figure B8 shows (Levy, 2018).

5.3 Labor Supply Elasticity across Sectors

The main parameter to estimate is the labor supply elasticity across sectors, κ, it governs the reallocation of workers from the informal to the formal economy. I build market access measures following Tsivanidis (2021) and Donaldson and Hornbeck (2016). These measures represent the wage index for each sector and capture whether workers obtained better access to formal jobs relative to informal jobs after the shock.

For this estimation, I calculate travel times across the different census tracts in Mexico City with and without Line B. I compute travel times for three different transportation modes: car, walking, and the public transit system.[33]

With the commuting times at hand, I define the commuter market access (CMA) for location n and sector s as $\text{CMA}_{ns} = W_{ns}^{\frac{1}{\theta_s}}$. This is an index of the accessibility of jobs in location n to employment in sector s. I solve the following system of equations to compute MA measures for both firms and workers:

$$\text{CMA}_{ns} = \sum_{i} \frac{\tilde{L}_{is} d_{ni}^{-\theta_s}}{\text{FMA}_{is}}, \quad \text{FMA}_{is} = \sum_{n} \frac{L_{ns} d_{ni}^{-\theta_s}}{\text{CMA}_{ns}}, \tag{5.4}$$

where $\tilde{L}_{is}$ represents total employment in location i and sector s; L_{ns} corresponds to the residents in location n and work in sector s; and FMA_{is} is a firm market access measure that captures whether firms in i have good access to workers from sector s.[34] After solving this system of equations, we can recover the wage distribution. Figure B10 plots the wage distribution.

The intuition of this system of equations follows the same logic as the case with only one sector. These measures capture whether residents from location n have good access to jobs from sector s, and similarly whether firms from location i have good access to labor.

Figure B11 plots ventiles of the change in CMA for both sectors after the transit shock, holding constant the number of workers and residents. It is clear that locations close to the new subway line improved their market access to both formal and informal employment relative to other census tracts in Mexico City. Additionally, Figure 3 plots natural breaks of the change in CMA, taking the difference between the formal and informal sector. It is clear that census tracts near line B experienced a larger increase in market access in the formal sector. Hence, workers in these census tracts obtained better access to formal jobs relative to the informal sector reallocating to firms with higher TFPR.

I exploit this variation to estimate the labor supply elasticity parameter across sectors. From

[33] I calibrate speeds for different types of roads and the public system using random trips from Google Maps. Table C1 describes the values obtained for each category and each mode of the transportation system.

[34] Tsivanidis (2021) estimates these measures for Bogotá and shows that with data of commuting costs, and the number of residents and workers in each sector and location, the system of equation 5.4 has a unique solution. Another way to prove the existence and uniqueness of this system of equations is to apply the theorem from Allen et al. (2015). The largest eigenvalue of this system of equations is 1. Thus, there is at most one strictly positive solution, up to scale with this system of equations.

the structure of the model, I derive a log-linear relationship between the commuter market access measures and the wage indices for each sector. In particular, $W_{ns}^{\theta_s} = \text{CMA}_{ns}$. Then, from equation 4.2, I estimate the following labor supply equation that correlates the change in the ratio between formal and informal residents with the change in CMA measures over time and across sectors:

$$\Delta \ln L_{nF,t} - \Delta \ln L_{nI,t} = \kappa \left(\frac{1}{\theta_F} \Delta \ln \text{CMA}_{nF,t} - \frac{1}{\theta_I} \Delta \ln \text{CMA}_{nI,t} \right) + \beta X_n + \gamma_{s(n)} + \epsilon_{nt}, \tag{5.5}$$

where Δ corresponds to the time difference between 2000 and 2010; $L_{nF,t}$, and $L_{nI,t}$ is the total number of residents that live in location n and work in the formal and informal sectors respectively; and $\gamma_{s(n)}$ is a municipality or state fixed effect. I include a vector of controls X_n to capture specific trends that vary with initial characteristics. To recover κ, equation 5.5 is akin to a triple difference estimator. The first difference corresponds to time variation before and after the transit improvements, the second difference exploits heterogeneity of the treatment across locations, and the third difference uses variation in the market access measures across sectors. As Figure 3 shows, Line B improved access to formal jobs for residents close to the new stations. It is important to mention that to estimate the parameter κ, the reallocation of workers wouldn't bias the estimate of κ since the model allows for migration within the city. Then, according to the model, I can estimate κ comparing census tracts over time.[35]

One caveat with the estimation of equation 5.5 is that the change in CMA may capture other shocks in the economy that shifts the allocation of labor across sectors and locations. For instance, the number of residents and workers can change in ten years due to other variables and shocks. For example, formal jobs can become less available if crime rates are growing in the treated locations. Therefore, these shocks can alter the decision of workers to operate in the formal or informal sector, thus, generating a correlation between the change in CMA and the error term. This generates a bias in the estimation of κ that, in principle, can be an upward or downward bias. To deal with this problem and capture only the change in the market access coming from the opening of Line B, I estimate equation 5.5 by two-stage least squares using two instruments. The first instrument is the change in the CMA measures when the number of residents and workers is fixed, and the second is the treatment dummy variable. The idea is to capture changes in commuting costs due to the new line and clean the estimation from other economic shocks and specific trends in the treated areas.

Table 4 reports the results for the labor supply elasticity across sectors. I obtained estimates of κ between 1.2 and 2.6. The first two columns show the results for the OLS and the other four columns for the IV using each instrument separately. In my preferred specifications, which are the ones in

[35] In particular even if the people reallocate, the comparison to estimate κ needs to be across census tracts after taking the ratio. The variable that determines who reallocates to the treated locations is $W_n = (W_{n\text{I}}^{\kappa} + W_{nF}^{\kappa})^{\frac{1}{\kappa}}$, and I am controlling for this variable after taking the ratio between the formal and the informal sectors since this wage index cancels out. Then, the reallocation of workers does not bias the estimation of κ since what matters is the share of formal to informal residents across census tracts even if there is migration.

columns 4 and 6, I obtained a point estimate between 1.6 and 2.6. For the counterfactuals, I take an average between these two numbers. Comparing the estimates from the 2SLS and OLS, it suggests that there were other shocks in the economy that created a downward bias for κ. For instance, these shocks reallocated workers from the informal to the formal sector generating a negative correlation between the change in the CMA measures and the error term.[36]

5.4 Labor and Capital Wedges

Labor and capital wedges are a crucial parameter for the quantitative analysis. I follow the popular approach from Hsieh and Klenow (2009) and Bau and Matray (2020), and use the inverse of the wage bill and capital shares to calibrate the distortions.[37] From the profit-maximization condition, the inverse of the labor and commercial floorspace share paid by each firm is:

$$\left(\frac{w_{is}l_{is}}{p_{is}y_{is}}\right)^{-1} = \frac{\sigma_s}{(\sigma_s - 1)\beta_s}\left(1 + t_{isL}\right), \qquad \left(\frac{q_{is}z_{is}}{p_{is}y_{is}}\right)^{-1} = \frac{\sigma_s}{(\sigma_s - 1)(1-\beta_s)}\left(1 + t_{isZ}\right)$$

where $w_{is}l_{is}$ is the wage bill, $q_{is}z_{is}$ is the commercial floorspace payments, and $p_{is}y_{is}$ are total sales. I can observe the left-hand side of this equation for each firm, and use the aggregate labor share β_s and markups in each industry to calibrate the wedges.[38] To aggregate from the firm level to the census-tract-sector cell, I take the mean of the inverse of the wage bill and capital shares across firms in each cell.

Figure B9 in the Online Appendix plots the labor-wedge distribution across locations for each sector in the baseline year. The wedges between the formal and informal sectors are very similar to the ones found by Busso et al. (2012). Formal firms face larger distortions. On average, the wedge in the formal sector is approximately 1.67 times the wedge in the informal sector. Furthermore, panel B of figure B12 in the Online Appendix shows the spatial distribution of labor wedges. In central locations, wedges are higher.

For the counterfactual analysis, I also use a more conservative wedge for formal firms based on the work from Levy (2018) (Table 7.9). For the labor wedge, I use a conservative value of 0.95, and for the commercial floor space, a value of 0.75. These wedges include several distortions such as implicit taxes on salaried workers, regulations on dismissals and reinstatements, non-contributory social insurance, standard labor taxation like state payroll taxes, and firm taxation including REPECO and value-added taxes.

[36] Relative to previous studies on estimating labor supply elasticities across sectors, such as Galle et al. (2017), Lagakos and Waugh (2013), and Berger et al. (2019), my estimates are similar.

[37] Other papers such as Busso et al. (2012) and Levy (2018) that have explored the role of resource misallocation in Mexico also use the same method. This is the most common approach used in the literature. For example, the literature that has focused on estimating markups from the production side assumes cost-minimizing firms and estimates markups using the inverse of the labor and capital shares (De Loecker and Goldberg, 2014).

[38] I am using the aggregate labor share to capture that distortions can vary for firms in different sectors.

5.5 Other Parameters

I calibrate other parameters of the model using simple moments of the data, or take them directly from the previous literature. I calibrate the expenditure share on housing using the ENOE and find a value of $\alpha = 0.75$. Similarly, for the labor share, I use aggregate data from the Economic Census in 1999 and find a value of $\beta_{\text{I}} = 0.70$, and $\beta_F = 0.60$. To calculate the total amount of housing $\tilde{H}$ and commercial floor space $\tilde{Z}$, I use the area in square kilometers of buildings in each census tract from the Global Human Settlement Layer (GHSL) in 2000 weighted by the total number of employees and residents. To calibrate the fixed costs, I use the log-linear relationship between the total number of firms and the workforce,and find $F_I = 0.15$, and $F_F = 1.2$. Section D.3 in the appendix specifies the details for this estimation. In addition, I use the estimate of the elasticity of substitution across sectors $\xi = 2$ from Edmond et al. (2015), which is similar to the estimates of other papers (Asturias et al., 2019). Also, I compute the counterfactuals using a value of $\eta = 1.50$ from Tsivanidis (2021) in Bogotá, a similar context to Mexico City.

5.6 Model Inversion

This section recovers the fundamental parameters B_n, B_{ns}, which capture differences in amenities that attract residents to each location and sector; and the productivity scale parameters A_{is}.

I proceed in three steps. In the first step, I recover relative differences in amenities and the wage distribution, equating the labor supply to actual data. In the second step, I obtain the productivity levels A_{is}, equating the labor demand to the number of workers in the data. In the third step, I recover the amenity parameters B_n, equating the residents' share in the model to the data.

Step 1: In a simultaneous step, I recover the entire wage distribution and the parameters B_{ns} by equalizing the labor supply from equation 4.4 to the total number of workers in each sector and location from the data. I assume without loss of generality that $B_{nI} = 1$. I identify B_{nF} from the following relationship using the share of informal workers from the data in each location and the wages:

$$\lambda_{nF|n} = \frac{B_{nF} \mathrm{W}_{nF}^{\kappa}}{B_{nF} \mathrm{W}_{nF}^{\kappa} + \mathrm{W}_{nI}^{\kappa}}.$$

I then identify the wage distribution by equalizing equation 4.4 to the number of workers from the data in the pre-period.

Step 2: Using the vector of wages, I recover the productivity parameters A_{is} by solving the labor demand from equation 4.17. I solve for the vector of productivities, equating the labor demand implied by the model to the number of workers in each sector and location from the data.

Step 3: With data on wages, and knowing the key elasticities, I can obtain the amenity parameters in each location B_n by equating the implied number of residents from the model with the number of residents from the data in the pre-period. In particular, I use λ_n from equation 4.2 in the model and equate it to the number of residents in the data.

Then, I compute trade flows and solve for the counterfactuals using exact hat algebra.[39]

6 Counterfactual Analysis

This section describes the counterfactual analysis. To compute the welfare effects of Line B, I calculate the commuting times with and without Line B. Then, I solve for the GE equilibrium before and after the shock. Regarding the distortions, I find a similar TFP effect as Busso et al. (2012), removing the wedges leads to productivity gains of around 200%.

I compute two different counterfactuals. The first one assumes that there is no migration within the city and only solves the goods market-clearing condition. The second ones takes into account the migration channel. I assume that the city is closed since the shock is only one line. This means that the total number of workers $\bar{L}$ is constant.[40] I calculate changes in welfare and total output using percentage changes. To decompose the welfare effects into the three terms, I compute the equilibrium with and without the labor wedge, and for the agglomeration channel, I assume a different value of σ_s in the two sectors.

Table 5 reports the results for the counterfactuals numbers. Columns 1-3 hold the number of residents constant, while columns 4-6 add the sorting mechanism. In panel B, I run the counterfactuals with a constant wedge for the formal sector. On average, Line B of the subway increased welfare between 1.5%-1.7%. Changes in commuting costs account for around 60% of the total gains, while changes in trade costs for the remaining 40%. In terms of the welfare decomposition, I find that in the case in which the distortions are calibrated using the data, the "direct" effect term represents approximately 78% of the total gains, the reallocation of workers to the formal sector explains 19%, and the agglomeration externality component drives the remaining 3%. Hence, the allocation mechanism generated 26% additional gains relative to the perfect economy. In the case in which I assume a constant wedge for the formal sector, the direct effect explains a larger fraction of the total gains, 83%; the change in factor allocation explains 14%, and differences in external economies of scale between the two sectors explain 3%. The results are robust for different values of η, κ, and ξ.[41]

The project's cost-benefit analysis implies that there was an increase of around 26% of real income net of the total cost at the aggregate level in the city. According to official documents from the Government, the total cost of Line B considering its net present value was approximately USD 2,900 million in 2014. This number represented approximately 0.72% of the total GDP of Mexico City. Then, in the benchmark case, line B generated an increase of around 2.22 USD per dollar spent on the infrastructure. This change would have been only 1.75 without considering the allocation

[39] Section E.3 in the Appendix provides the equilibrium conditions of the model with exact hat algebra.

[40] Since I am only analyzing the effect of one line, it is very plausible that the population of the city did not change because of the shock.

[41] The results are available upon request.

mechanism. The new margin increased the effect on total welfare by more than 25%.[42] For instance, if the city constructs a line or a road with a similar demand, but in places in which most of the workers are formal, the changes in welfare are smaller. I now explore the role of other policies to reduce informality.

Entry fixed costs: First, I consider a policy in which the Government reduces the entry fixed cost of formal firms or increases it for informal firms. These policies are akin to making it easier for entrepreneurs to start a formal business (i.e., reducing red tape) or to increase government regulations for the entry of informal firms.

According to the model, Line B of the subway led to a decrease in informality rates at the aggregate level by 0.5%. Figure 4 plots the effectiveness of different policies that change the entry fixed cost for both formal and informal firms.

There are three main takeaways from this analysis. First, it is more effective to reduce the entry fixed cost of formal firms relative to increasing the entry fixed cost of informal firms. This suggests that it would be more efficient to focus on policies that benefit formal firms than to harm informal firms. Second, as the target of the Government increases, it becomes more effective to reduce the formal fixed cost relative to increasing the informal fixed cost. Third, transit infrastructure that connects informal workers with formal employment can be a useful tool to reduce informality. For example, if the government wants to generate similar results at the aggregate level, it needs to change the fixed cost by a substantial proportion (more than 10%).

Place-based policies: For the second set of policies, I study whether place-based policies that reallocate formal firms in the city can effectively increase welfare and reduce informality. The intervention consists of increasing the commercial floor space employed by formal firms in different parts of the city. I consider two sets of policies; the first one consists of increasing the commercial floor space in the CBD, and the second one in the outskirts. Figure B15 plots the locations in which the Government implements the policy; in total, there are 250 treated census-tracts in both parts of the city. The goal is to compare policies that reallocate formal firms to the outskirts (de-agglomeration policies) vs. transit shocks that connect informal workers with formal jobs.

Figure 5 plots the results of the intervention. In panel A, the Government increases commercial floor space in the central locations, and in panel B in the remote areas. The results suggest that it is more effective to intervene in the central locations than in the outskirts. For instance, if the Government increases the commercial floor space by 40% in the central areas, the policy generates similar welfare gains to the transit shock that I studied. On the other hand, as shown in panel B, it is very ineffective to reallocate firms to the outskirts. Even if the Government increases the commercial floor space by a substantial proportion, 60%, it only increases welfare by 0.18%, which

[42] This number is obtained in the following way: in the perfectly efficient economy, the total gains are: 1.26% of the GDP, then the benefit per dollar spent on the project is 1.75 (1.26/0.72). On the other hand, under the inefficient economy, the benefit is 1.6%, and the value per dollar spent on transit infrastructure is 2.22 (1.60/0.72). Thus, there was an increase of 26.9% relative to the perfectly efficient economy.

is significantly lower than the one obtained by the new subway line. Moreover, in the latter case, the allocative efficiency margin and the externality component explain a very small fraction of the total gains.

There are two main explanations for this result. The first one is that since most formal firms are located in the CBD, the agglomeration forces are negligible in the outskirts. The second one is that these locations are very unproductive regarding the productivity scale parameters, especially for formal firms. Hence, reallocating firms to the outskirts do not generate sizeable welfare gains.

7 Conclusion

This paper has examined the welfare gains from transit improvements in developing countries, considering the allocative efficiency margin driven by the highly inefficient informal sector. I find that transit infrastructure facilitating commuting may generate additional welfare gains by improving the market access of the informal labor force to formal employment.

From an empirical perspective, the paper exploits a transit shock in Mexico City that connected poor and remote areas with the city's center. The main finding is that informality rates decrease in the locations that experienced the shock relative to other places in the city. This result implies that workers reallocated to firms with higher TFPR, thereby increasing welfare to a larger extent than the predictions under perfectly efficient economies.

On the quantitative side, the paper departs from the standard efficiency case in urban models that have studied the economic impact of transit infrastructure. The model extends the basic framework by adding wedges and resource misallocation and providing a welfare decomposition formula from a first-order approximation. The paper quantifies the gains from transit infrastructure and finds that allocative efficiency drives approximately 17%-25% of the total gains.

The results from this study are informative to policymakers in several aspects. It is essential that when they analyze the benefit and opportunity cost of a project, they take into consideration other first-order effects that are driven not just by the direct effects through the classic approach of transportation demand but through allocative efficiency. For example, policymakers should consider whether the population residing in the potentially connected areas works in the informal or formal economy. The findings imply that even if a government is not concerned about distributional aspects, connecting poor areas with high-efficiency locations can generate larger gains than transit developments that link locations with a similar composition of workers.

The findings are also informative on other public policy aspects in urban areas. Programs that segregate informal workers and poor individuals in developing countries, combined with the high commuting costs, can increase the extent of resource misallocation, lowering aggregate efficiency and TFP. Hence, governments must make decisions based on an analysis considering all the first-order components that may affect welfare, especially in economies with distortions.

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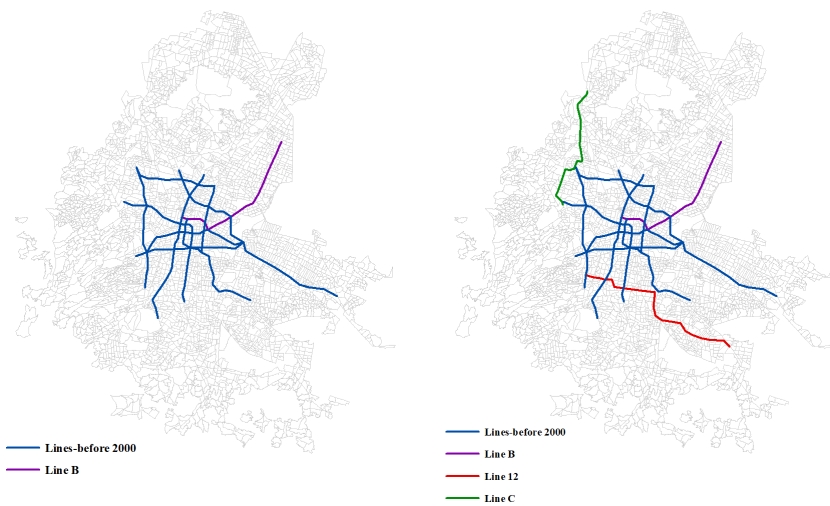
Figures

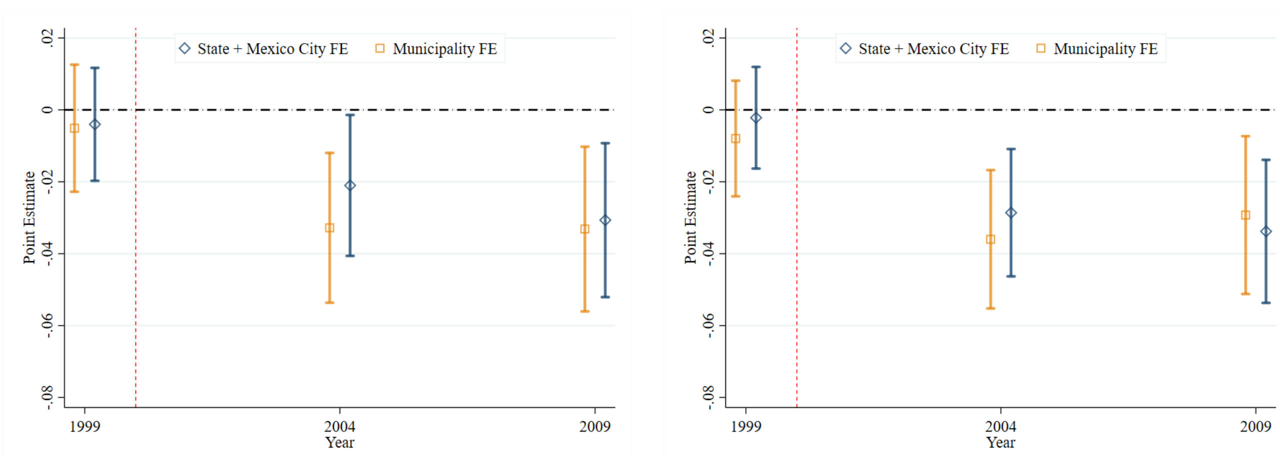
Figure 1: Transit System



(a) Line B (b) Other lines

Notes: This figure plots a map of Mexico City with the transportation system. Panel (a) highlights the transit line -Line B- that I exploit in my main specification. On the other hand, panel (b) highlights the two lines that I use as a control group for the robustness checks. According to the transit expansion plan from 1980, line c -green line- was planned as a feeder line in the early 2000s, similar to line B. However, the Government of the city never constructed it. And line 12 -red line- is the latest subway line in Mexico City and was opened in 2012. The other lines correspond to the other subway lines of the actual system.

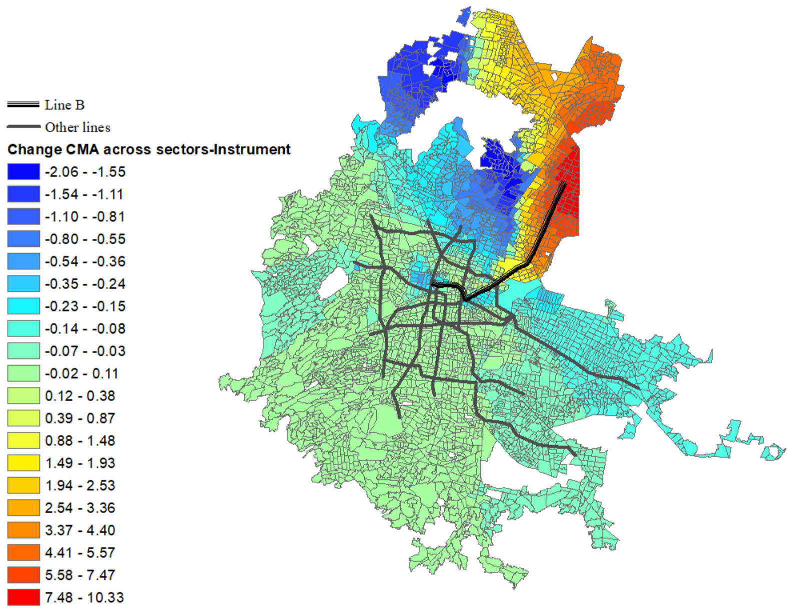
Figure 2: Difference in Difference Results-Workers' Informality Share



(a) Informal workers (b) Informal and non-salaried workers

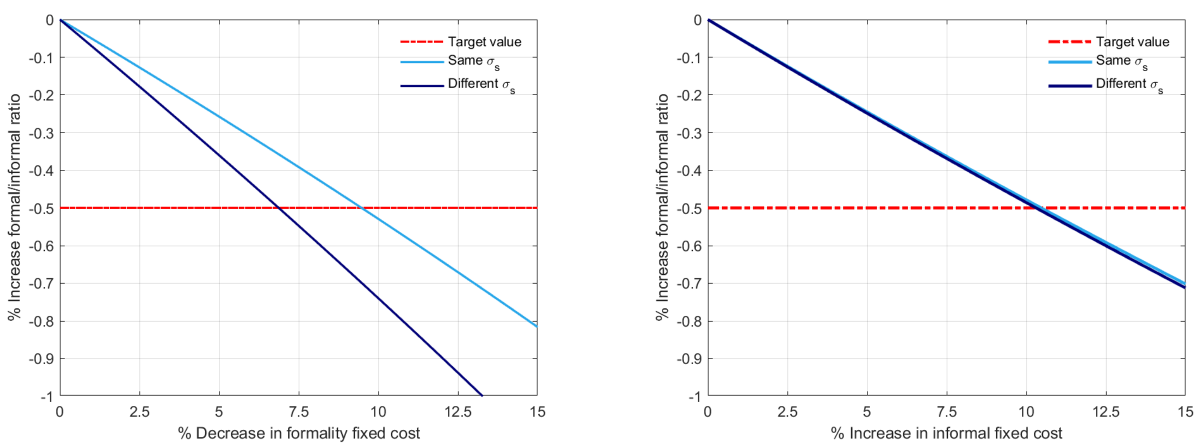
Notes: This figure depicts the point estimates and 90th percentile confidence interval from the difference in difference specification relating workers' informality rates with the transit shock. The treatment group are census tracts with centroids within a walking range of 25 minutes to stations of line B. The control group are census tracts in Mexico City. Panel (a) reports the results for the share of informal workers, and panel (b) for the share of informal and non-salaried workers. Standard errors are clustered at the census tract level.

Figure 3: Change in CMA across sectors



Notes: This figure plots a heat map of Mexico City with the spatial distribution of the change in CMA across sectors after the transit shock holding the number of workers and residents fixed. I construct natural breaks across locations by taking the difference between the formal and informal sector of CMA before and after the shock. Each color represents one of the natural breaks categories. Blue colors represent a very small change, while red color a very large change. From the figure, census tracts close to the new line got better access to formal employment relative to the informal sector. Thus, workers reallocate to the formal sector.

Figure 4: Counterfactual results-Fixed costs

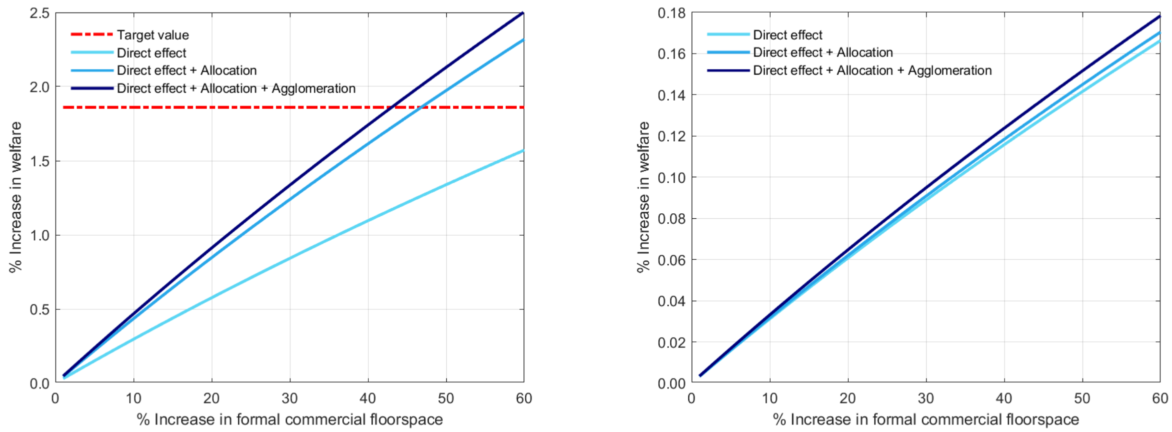


(a) Decrease formal costs

(b) Increase informal costs

Notes: This figure plots the counterfactual results for changes in the entry fixed cost for both formal and informal firms. Panel (a) shows the results for a counterfactual reducing formal fixed costs, and panel (b) for a counterfactual increasing informal fixed costs. The objective of the government is to reduce informality rates by 0.5%, which is the aggregate effect that I find from the transit shock.

Figure 5: Counterfactual results-Place based policies



(a) Place-based policies central locations

(b) Place-based policies remote locations

Notes: This figure plots the counterfactual results for changes in the supply of commercial floor space for formal firms. Panel (a) shows the results for a counterfactual increasing commercial floor space in central locations, and panel (b) in remote areas. The objective of the government is to increase welfare by 1.84%, which is the effect from the transit line.

Tables

Table 1: Difference-in-Difference - Share of Informal Residents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome:	$\Delta(\ln L_F - \ln L_I)$	$\Delta(\ln L_F - \ln L_I)$	$\Delta(\ln L_F - \ln L_I)$	$\Delta(\ln L_F - \ln L_I)$	$\Delta(\ln L_F - \ln L_I)$	$\Delta(\ln L_F - \ln L_I)$	$\Delta(\ln L_F - \ln L_I)$	$\Delta(\ln L_F - \ln L_I)$
			Panel A: Continuous treatment measure-Pool of residents					
- ln distance	0.040***	0.054***	0.045***	0.058***	0.014*	0.030***	0.018**	0.035***
	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)
Observations	3,192	3,192	3,192	3,192	3,192	3,192	3,192	3,192
R-squared	0.162	0.248	0.162	0.248	0.230	0.300	0.230	0.301
			Panel B: Treatment dummy variable-Pool of residents					
T_i	0.038**	0.069***	0.033**	0.067***	0.024	0.068***	0.016	0.064***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.018)	(0.016)	(0.018)	(0.017)
Observations	3,192	3,192	3,192	3,192	3,192	3,192	3,192	3,192
R-squared	0.156	0.241	0.156	0.240	0.230	0.300	0.230	0.300
			Panel C: Continuous treatment measure-Low skilled residents					
-ln distance	0.049***	0.056***	0.053***	0.060***	0.017*	0.032***	0.021**	0.036***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)	(0.010)	(0.009)
Observations	3,192	3,192	3,192	3,192	3,192	3,192	3,192	3,192
R-squared	0.137	0.230	0.138	0.230	0.203	0.281	0.203	0.282
			Panel D: Treatment dummy variable-Low skilled residents					
T_i	0.051***	0.071***	0.046***	0.069***	0.027	0.068***	0.019	0.065***
	(0.017)	(0.016)	(0.017)	(0.016)	(0.019)	(0.017)	(0.019)	(0.017)
Observations	3,192	3,192	3,192	3,192	3,192	3,192	3,192	3,192
R-squared	0.130	0.222	0.130	0.221	0.202	0.281	0.202	0.281
			Panel E: Continuous treatment measure-Outskirt area					
-ln distance	0.072***	0.088***	0.079***	0.095***	0.037***	0.050***	0.041***	0.055***
	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)	(0.009)	(0.011)	(0.010)
Observations	2,171	2,171	2,171	2,171	2,171	2,171	2,171	2,171
R-squared	0.199	0.279	0.200	0.279	0.279	0.338	0.280	0.338
			Panel F: Treatment dummy variable-Outskirt area					
T_i	0.076***	0.138***	0.066***	0.131***	0.062***	0.110***	0.048**	0.099***
	(0.021)	(0.019)	(0.022)	(0.019)	(0.023)	(0.021)	(0.024)	(0.022)
Observations	2,171	2,171	2,171	2,171	2,171	2,171	2,171	2,171
R-squared	0.185	0.264	0.184	0.262	0.277	0.336	0.276	0.335
Distance	Meters	Minutes	Meters	Minutes	Meters	Minutes	Meters	Minutes
Dist.+Prod. Controls	X	X	X	X	X	X	X	X
Population Controls		X		X		X		X
State FE	X	X	X	X				
Municipality FE					X	X	X	X

Notes: This table reports the results of a regression relating changes in the share of informal residents in each location with the line B of the subway. Panel A reports the results for the continuous treatment measures and the pool of residents, panel B for the treatment dummy variables and the pool of residents, panel C for the continuous treatment measure and low-skilled workers, panel D for the treatment dummy variables and low skilled workers, panel E for the continuous treatment measure on the locations that are not in the CBD, and panel F for the treatment dummy variable on the locations that are not in the CBD. In the first four columns, I include state-time fixed effects, and in the fifth column to the eight column municipality-time fixed effects. The regressions are weighted by the population in 2000. Standard errors are clustered at the census tract level and reported in parentheses. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table 2: Change in covariates after the transit shock

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome:	Number of kids				Household size			
- ln distance	0.008		-0.004		0.015		0.011	
	(0.042)		(0.052)		(0.013)		(0.014)	
T_i		-0.026		-0.049		0.024		0.011
		(0.091)		(0.104)		(0.030)		(0.029)
Observations	3,192	3,192	3,192	3,192	3,192	3,192	3,192	3,192
R-squared	0.038	0.038	0.076	0.076	0.060	0.060	0.076	0.076
Outcome:	Male dummy				Age			
- ln distance	0.000		-0.000		-0.008		0.031	
	(0.000)		(0.000)		(0.021)		(0.026)	
T_i		-0.001		-0.002***		0.008		0.107*
		(0.001)		(0.001)		(0.050)		(0.057)
Observations	3,192	3,192	3,192	3,192	3,192	3,192	3,192	3,192
R-squared	0.255	0.255	0.273	0.273	0.137	0.137	0.179	0.180
Outcome:	High-skilled share				Student share			
- ln distance	-0.000		-0.001		-0.002**		-0.001	
	(0.001)		(0.001)		(0.001)		(0.001)	
T_i		-0.002		-0.001		-0.006***		-0.004**
		(0.002)		(0.002)		(0.002)		(0.002)
Observations	3,192	3,192	3,192	3,192	3,192	3,192	3,192	3,192
R-squared	0.244	0.244	0.310	0.310	0.142	0.143	0.174	0.175
Controls	X	X	X	X	X	X	X	X
State FE	X	X			X	X		
Municipality FE			X	X			X	X

Notes: This table reports the results of a difference-in-difference specification relating changes in household composition and covariates with the transit shock. The odd columns report the results for the continuous treatment variable, and the even columns for the treatment dummy variable. The regressions are weighted by the population in 2000. Standard errors are clustered at the census tract level and reported in parentheses. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 3: Gravity Equations-Commuting and Trade Elasticities

	(1) Formal sector	(2) Informal sector
	Panel A: commuting	
Outcome	$\ln \lambda_{niF}$	$\ln \lambda_{niI}$
Minutes	-0.028***	-0.042***
	(0.003)	(0.005)
Observations	2,257	2,280
R-squared	0.535	0.518
Implied θ	**3.11**	**5.12**
	Panel B: Trade	
Outcome	$\ln \pi_{niF}$	$\ln \pi_{niI}$
Minutes	-0.059***	-0.078***
	(0.004)	(0.005)
Observations	2,128	2,108
R-squared	0.406	0.497
Implied σ	**6.08**	**7.81**
Origin -Transportation mode FE	X	X
Destination -Transportation mode FE	X	X

Notes: This table reports the results of a gravity equation relating commuting and trade flows at the municipality level with the average time for four different transportation modes: car, bus, metro or metrobus (brt), and walking. I estimate this regression via the PPML method to include the zeros. The first column presents the results for the formal sector the second column for the informal sector. Standard errors are clustered at the municipality of origin level and reported in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table 4: Estimation of Labor Supply across sectors

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	IV1	IV1	IV2	IV2
Outcome:	$\Delta_{t,s} \ln L_s$	$\Delta_{t,s} \ln L_s$	$\Delta_{t,s} \ln L_s$	$\Delta_{t,s} \ln L_s$	$\Delta_{t,s} \ln L_s$	$\Delta_{t,s} \ln L_s$
κ	0.132**	-0.367***	1.246***	1.686***	1.431***	2.602***
	(0.067)	(0.092)	(0.158)	(0.244)	(0.343)	(0.724)
Observations	3,192	3,192	3,192	3,192	3,192	3,192
Adjusted R-squared	0.237	0.296	-	-	-	-
			FS1	FS1	FS2	FS2
Outcome:			$\Delta_{t,s}$ CMA	$\Delta_{t,s}$ CMA	$\Delta_{t,s}$ CMA	$\Delta_{t,s}$ CMA
$\Delta_{t,s}$CMA			2.033***	1.431***		
			(0.158)	(0.244)		
T_i					0.049***	0.026***
					(0.004)	(0.003)
Observations			3,192	3,192	3,192	3,192
Adjusted R-squared			0.541	0.842	0.501	0.822
F-stat			312.20	292.14	145.41	65.01
Controls	X	X	X	X	X	X
State FE	X		X		X	
Municipality FE		X		X		X

Notes: This table reports the results of the estimation of the labor supply elasticity to recover the parameter κ, which governs the reallocation from the informal to the formal sector. The dependent variable is the change in the log ratio between formal and informal workers. The independent variable is the change in CMA across sectors. The first two columns show the results for the OLS. The third and fourth column displays the results of a two-stage least square estimation using as an instrument the change in CMA across sectors and holding constant the number of workers and residents. The fifth and sixth column display the results of a two-stage least square estimation using as an instrument a dummy variable indicator of whether the centroid of the census tract is within a 25 minute walking range. The odd columns include state fixed effects, and the even columns include municipality fixed effects. Standard errors are clustered at the census tract level and reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5: Counterfactual Results $\hat{X} = X'/X$

	(1)	(2)	(3)	(4)	(5)	(6)
		No Migration			Migration	
	Panel A: Percentage change in welfare-Distortions					
%Δ **Welfare**	Δd_{ni}	$\Delta \tau_{ni}$	$\Delta d_{ni}, \Delta \tau_{ni}$	Δd_{ni}	$\Delta \tau_{ni}$	$\Delta d_{ni}, \Delta \tau_{ni}$
Total change	0.92%	0.65%	1.69%	0.89%	0.62%	1.59%
Decomposition						
Pure Effect	90.97%	64.85%	79.27%	90.62%	64.83%	79.25%
Allocation	8.09%	31.18%	18.89%	8.20%	30.70%	18.47%
Agglomeration	0.94%	3.97%	1.84%	1.18%	4.47%	2.29%
	Panel B: Percentage change in welfare-Constant wedge					
%Δ **Welfare**	Δd_{ni}	$\Delta \tau_{ni}$	$\Delta d_{ni}, \Delta \tau_{ni}$	Δd_{ni}	$\Delta \tau_{ni}$	$\Delta d_{ni}, \Delta \tau_{ni}$
Total change	0.90%	0.60%	1.60%	0.87%	0.57%	1.52%
Decomposition						
Pure Effect	92.68%	70.86%	83.79%	91.74%	70.18%	82.87%
Allocation	6.48%	23.25%	13.72%	7.20%	23.41%	14.21%
Agglomeration	0.84%	5.90%	2.50%	1.07%	6.41%	2.91%

Notes: This table reports the counterfactual results for the line B of the subway. The first and fourth column considers only change in commuting costs, the second and fifth column changes in trade costs, and the third and sixth column considers changes in both type of iceberg costs. The first three columns presents the results for the counterfactual with no migration, and the second three columns for the counterfactual in which I allow for migration in the model. Panel A reports the results for welfare with the calibrated distortions a lá Hsieh & Klenow (2009), and panel B for welfare with a constant wedge in the formal sector based on Levy (2018). The first row describes the results considering the total change. While, the other rows decompose the total change into the different components. The second row shows the percentage explained by the direct effect, the third row by the allocative efficiency margin, and the fourth row by the agglomeration externality component.

For Online Publication: Appendix
Spatial Misallocation, Informality, and Transit Improvements

A Empirical Facts

In this section, I discuss two facts in the data that show a negative relationship between the accesibility of formal jobs and informality.

Finding 1: *Most formal jobs are located in the central areas of the city, while most informal workers reside in the outskirts.*

The first fact is that most formal jobs are available in the center and west of the city, while informal workers reside in other, less connected areas. As a consequence, workers that cannot afford the high rents in the center of the city, live in outlying areas with poor access to formal jobs.

Figure B4 shows a heat map of informality rates in Mexico City and adjacent municipalities in the State of Mexico in terms of jobs and the residence of workers. Panel A in figure B12 shows that the west and the center of Mexico City have the highest level of economic activity.[43] Combining these two figures, we see that informality rates are lower in the west and the center of the city than in the east and the periphery of the city. One potential explanation of this result is that workers in the outskirts have poor access to formal jobs relative to informal employment.

Finding 2: *Informal workers spend less time commuting and work closer to their home relative to formal workers.*

To show this finding, I use the 2015 Intercensal Survey. With this data, I observe the residence and workplace and average commuting time of each worker at the municipality level. Exploiting cross-sectional variation, I compare the average commuting time and the workplace decisions of informal vs. formal workers. I restrict the sample to individuals who worked the week before the census interview and run the following linear probability model to test whether informal workers spend less time commuting:

$$y_i = \beta_0 + \beta_1 \text{Informal}_i + \gamma X_i + \gamma_{l(i)} + \gamma_{n(i)} + \gamma_{m(i)} + \epsilon_i, \tag{A.1}$$

where y_i is a dummy variable that takes the value of 1 if individual i commutes to a different municipality than the one in which he/she resides, whether he/she works in the central business district (CBD), or whether their average commuting time is within some window of time (i.e., 16 to 30 minutes); X_i is a vector of individual characteristics that includes age, education, gender, relationship to head of household, and a dummy variable indicating whether the individual indigenous background; $\gamma_{l(i)}$ and $\gamma_{n(i)}$ are origin and destination fixed effects; $\gamma_{m(i)}$ is a transportation mode fixed effect to compare informal vs. formal workers that use the same transportation mode; and, ϵ_i is the error term of the regression.

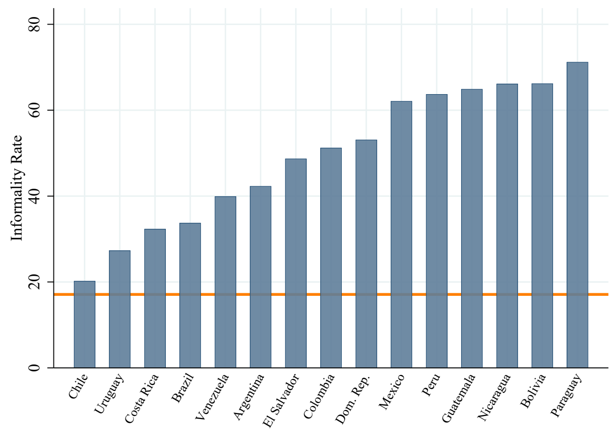
Figure B3 depicts the point estimate and confidence interval of a linear probability model. I relate the probability that the average commuting time of a worker is within some window of time with an informal dummy variable. As the figure shows, informal workers spend less time commuting than formal workers. The first two bars shows that informal workers are more likely to work from their home or spend less than 15 minutes commuting, while formal workers are more likely to spend more than 30, 60, or 120 minutes commuting.

To provide more evidence of this result, table C1 reports the results for the dummy variables of whether the worker commutes to another municipality; and whether he/she works in Mexico City. The results imply that informal workers are less likely to commute to a different municipality or work in the CBD.

[43] Panel B in figure B12 shows that the labor wedge in these locations is higher.

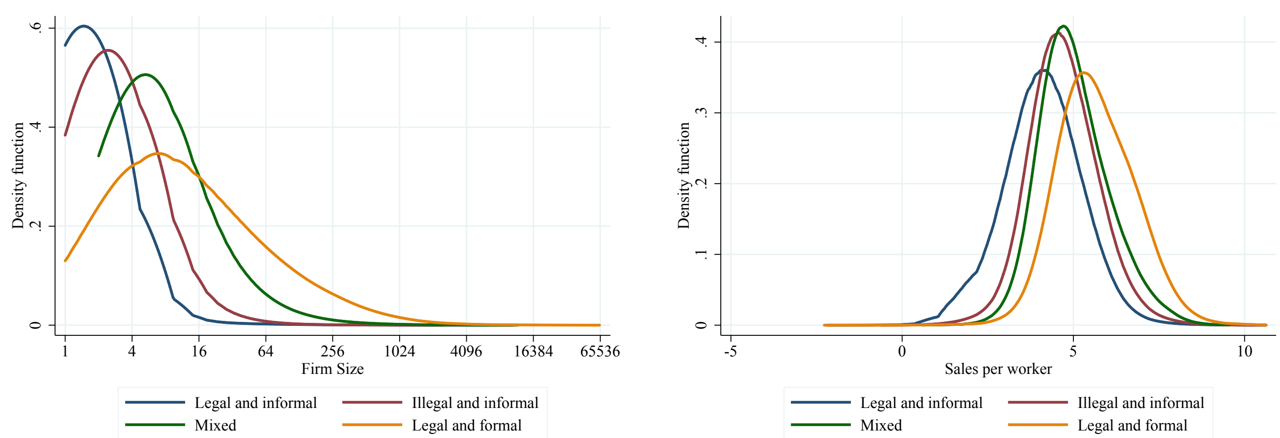
B Additional Figures

Figure B1: Informality Rates-Latin America and the Caribbean



Notes: This figure plots informality rates across countries from Latin America and the Caribbean. The data source is the online appendix from Ulyssea (2018) that uses data from *SEDLAC*, an initiative from the World Bank and Universidad Nacional de la Plata. Informal workers are defined as those without social security. The orange line represents the average informality rate of countries from the OECD. The figure shows that informality rates in LAC are very high, and even within the region, Mexico is one of the countries with the highest informality rates.

Figure B2: Firm size and Productivity Distribution-Economic Census 1999

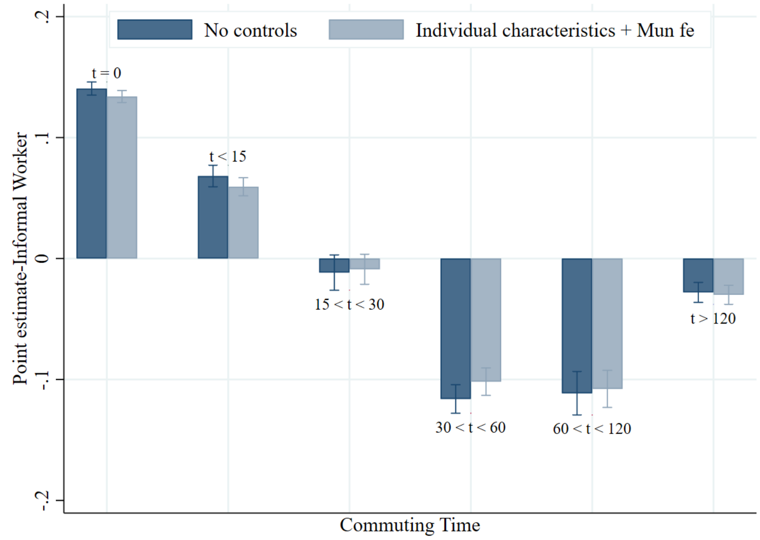


(a) Firm size

(b) Productivity

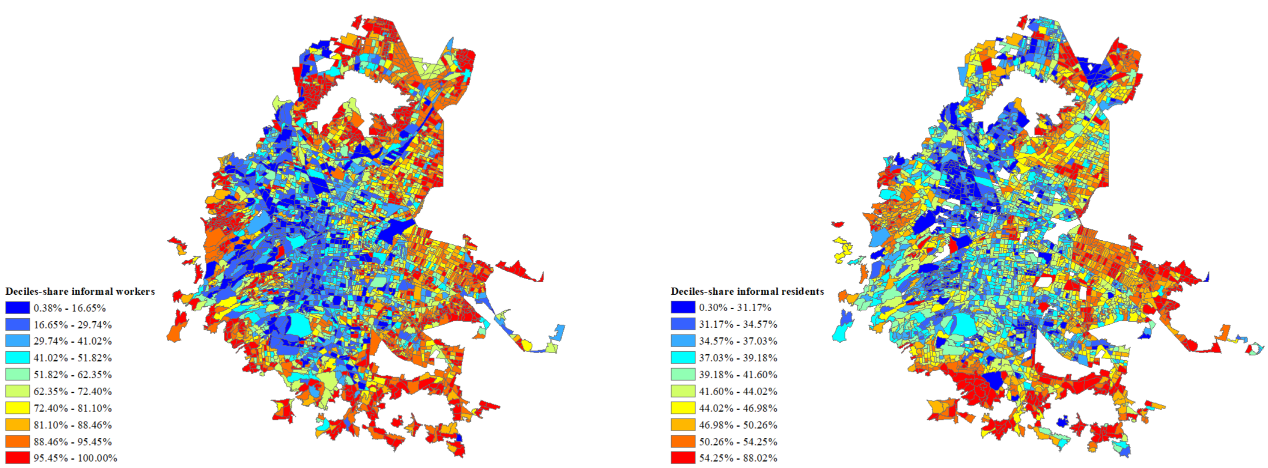
Notes: This figure plots the firm size and productivity distribution for the four different categories of firms: 1) Legal and informal 2) Illegal and informal, 3) Mixed, and 4) Legal and formal. I use the 2004 economic census. Panel (a) plots the firm size distribution and panel (b) the productivity distribution. Firm size is measured as the number of workers, and productivity as the logarithm of sales per worker.

Figure B3: Commuting Time- Informal vs. Formal



Notes: This figure plots the point estimate and 95th percentile confidence interval of a regression that relates the probability of commuting within some window of time with an informal dummy variable. The first bar reports the results for the category of non-commuting, the second bar if the worker spends on average between 1 to 15 minutes, the second bar between 16 to 30 minutes, the fourth bar between 30 to 60 minutes, the fifth bar between 60 to 120 minutes, and the sixth bar more than 120 minutes. The dark-blue bar does not include controls, while the light-blue bar includes individual controls and municipality fixed effects. Standard errors are computed with clusters at the municipality level.

Figure B4: Spatial distribution of informality

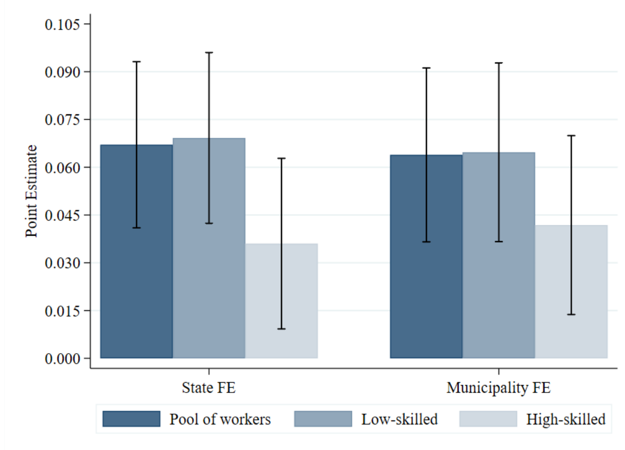


(a) Informal workers

(b) Informal Residents

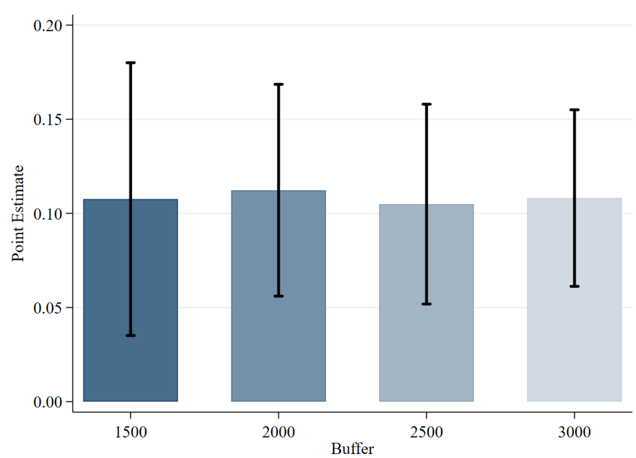
Notes: This figure plots a map of Mexico City with the spatial distribution of informality rates. Panel (a) plots a heat map of workers' informality rates by deciles in 1999. Panel (b) plots a heat map of residents' informality rates by deciles in 2000. The main takeaway of this map is that in the middle-west and center of the city informality rates are lower than on the boundaries and east of Mexico City. As a result, informal workers that live in the outskirts have poor access to most of the formal employment, which is located in the center of the city.

Figure B5: Difference in Difference Results-Residents' Informality Share



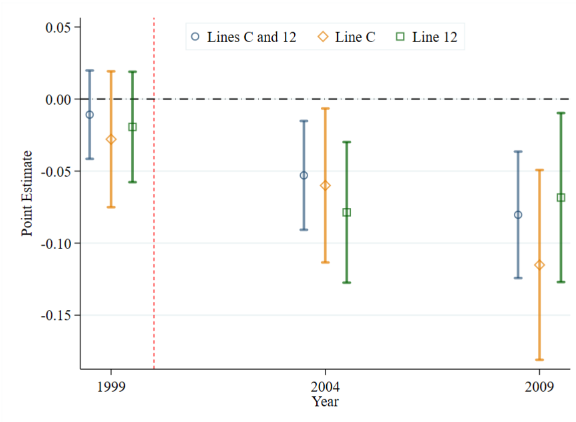
Notes: This figure depicts the point estimate and 90th percentile confidence interval of a regression that relates the change over time in the log of the ratio between formal and informal residents with the transit shock. The treatment variable takes a value of 1 for census tracts with a centroid within a 25 minutes walking range. The first three bars show the results of a regression including distance and population controls with state fixed effects, and the second three bars report the results with municipality fixed effects. Standard errors are clustered at the census tract level. The dark-blue bar reports the results for the pool of workers, the middle-blue bar for low-skilled workers and the light-blue bar for high skilled workers. Line B increased the ratio of formal to informal residents on approximately 7% when I compare treated areas vs. the rest of Mexico City.

Figure B6: Robustness Checks-Residents' Informality Share

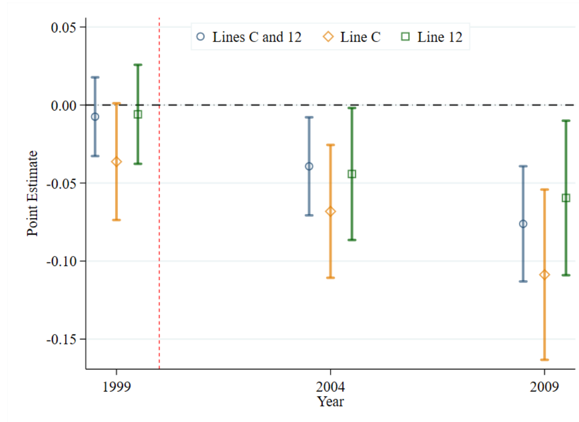


Notes: This figure depicts the point estimate and 95th percentile confidence interval of a regression that relates the change over time in the log of the ratio between formal and informal residents with the transit shock. The treatment variable takes a value of 1 for census tracts whith a centroid within a buffer zone of the new subway line. The control group are locations within a buffer zone of line C or line 12. These were subway lines that the Government planned to build in the 1980s, but it didn't construct in my period of analysis. I use different buffer zones: 1500, 2000, 2500, and 3000 meters. The first bar shows the results for 1500 meters, the second bar for 2000 meters, the third bar for 2500 meters, and the fourth bar for 3000 meters. Standard errors are clustered at the census tract level.

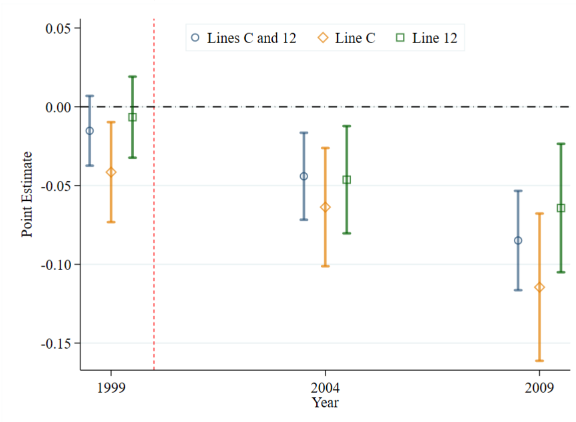
Figure B7: Robustness checks-Workers' Informality Share



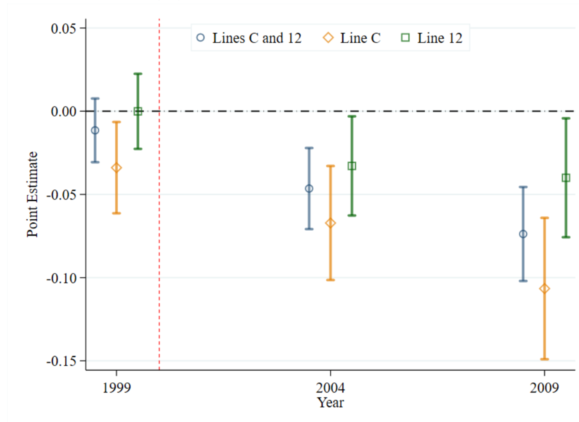
(a) Buffer: 1500 meters



(b) Buffer: 2000 meters



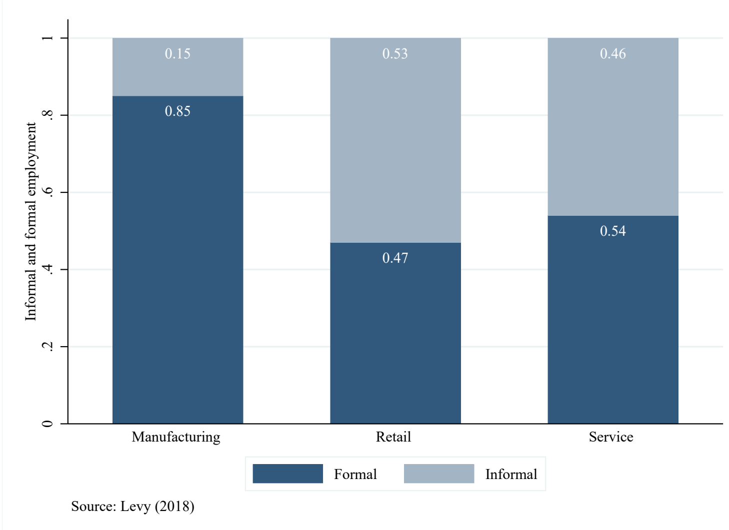
(c) Buffer: 2500 meters



(d) Buffer: 3000 meters

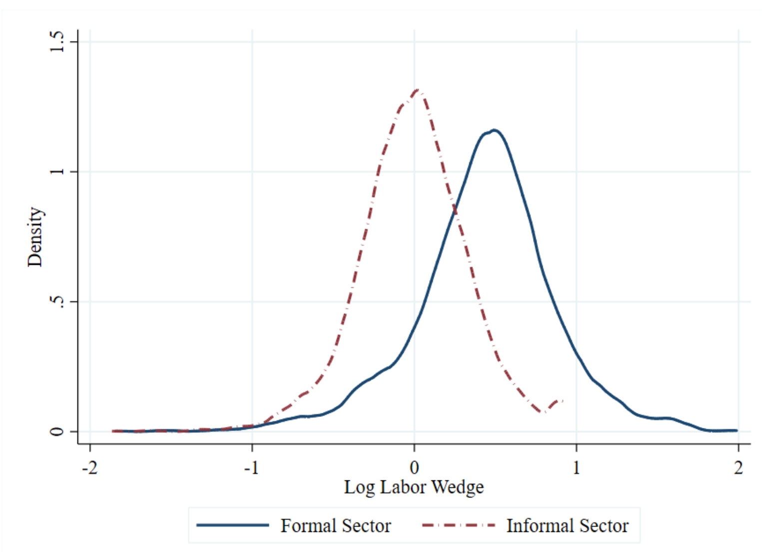
Notes: This figure depicts the point estimates and 95th percentile confidence interval from the difference-in-difference specification using different buffers and different control groups. The treatment group is defined as census tracts that are within a buffer to the new stations. The control group are census tracts within a buffer to lines that the Government planned to build in 1980, but that were not constructed in my period of study. The outcome variable is the share of informal and non-salaried workers and the specification includes state-time fixed effects. Panel (a) reports the results for a buffer of 1500 meters, panel (b) for 2000 meters, panel (c) for 2500 meters, and panel (d) for 3000 meters. The blue line pools together as a control group the locations close to line C and line 12, the orange lines locations close to line C, and the green line are locations close to line 12. Standard errors are clustered at the census tract level.

Figure B8: Informal/formal sector by industry



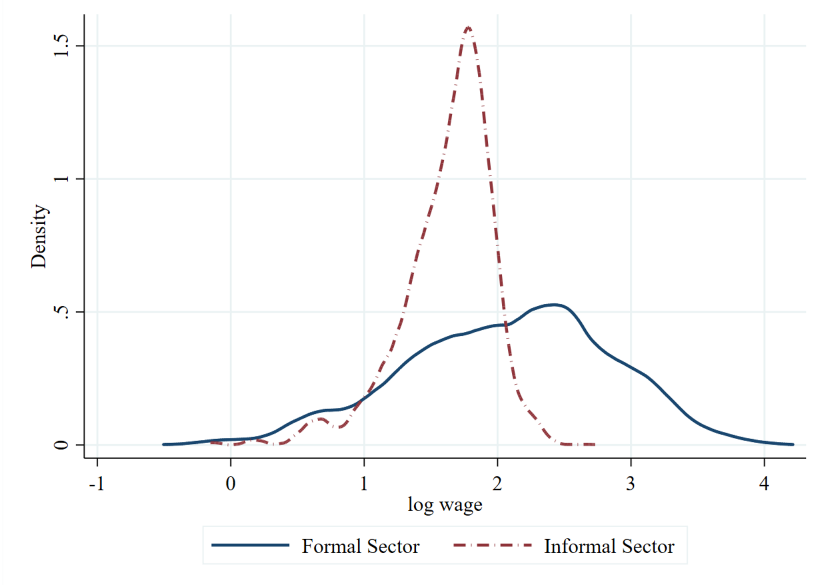
Notes: This figure plots the share of employment by industry between the formal and informal sector. The information comes from the book by Levy (2018), who uses the 2014 Mexican Economic Censuses. In his book, like this study, the author defines the informal and formal sector using the contractual relationship between the firm and the worker. An establishments is informal if it only hires non-salaried workers or if it does not provide social security to their workforce.

Figure B9: Distribution of Labor Wedges by Sector



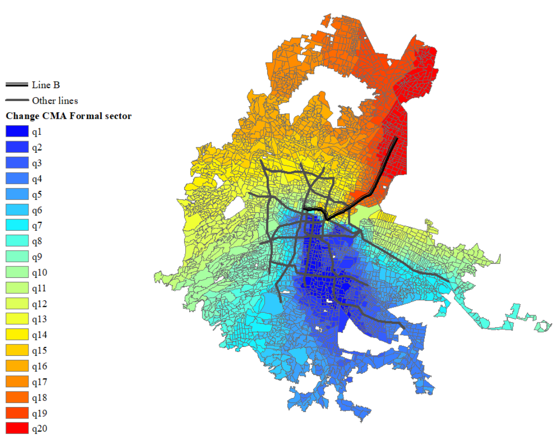
Notes: This figure plots the distribution of the labor wedge by sector across the different census tracts. I follow Hsieh and Klenow (2009) to calculate the labor wedge for each sector-location cell using the inverse of the labor share. In particular the distortion is computed using the following relations $\frac{w_{is}L_{is}}{p_{is}y_{is}}$. The blue line depicts the labor wedge distribution for the formal sector, and the red line for the informal sector. The figure suggests that conditional on productivity, formal firms are too small relative to a perfectly efficient allocation since these firms have higher levels of total factor revenue productivity (TFPR). The marginal revenue product of labor does not equalize across firms.

Figure B10: Distribution of Wages by Sector

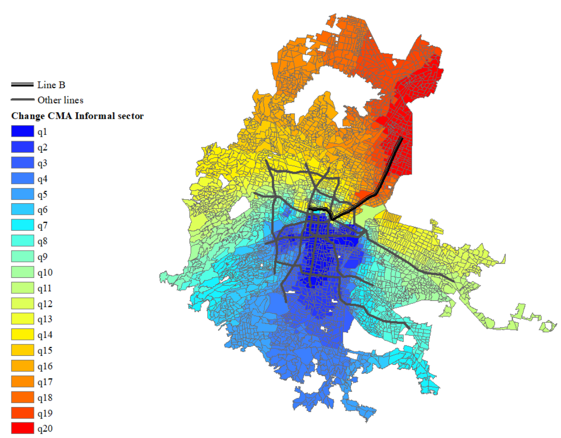


Notes: This figure plots the wage distribution obtained from the market access measures and the number of workers in each census tract. According to the definition of firm market access, $w_{is}^{\theta_s} = L_{is}\text{FMA}_{is}^{-1}$. The blue line depicts the wage distribution for the formal sector, and the red line for the informal sector. The model replicates that the formal sector pays a wage premium. This value is approximately 55% by comparing the wage median between the formal and informal sector.

Figure B11: Change in CMA for each sector



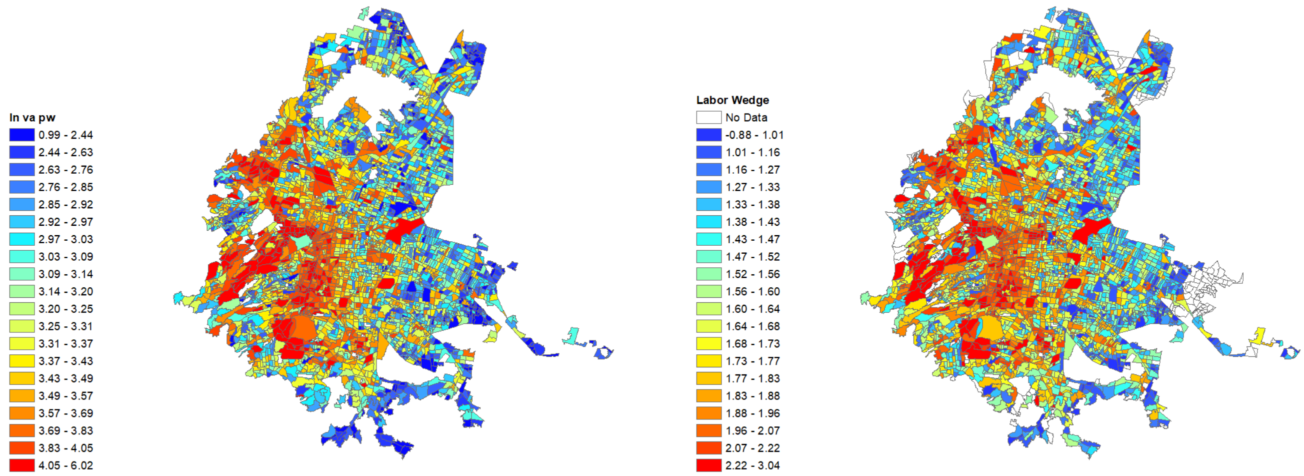
(a) Δ CMA Formal Sector



(b) Δ CMA Informal Sector

Notes: This figure plots a map of Mexico City at the census tract level with the spatial distribution of the change in CMA after the transit shock for each sector. I construct ventiles for the change in CMA across locations before and after the transit shock. Each color represents one quantile category. Blue colors represent a very small change, while red color a very large change. Panel (a) plots a heat map for the formal sector, and panel (b) for the informal sector. From the figure, it is clear that locations that experienced the shock and are close to the new stations got better access to both formal and informal employment.

Figure B12: Spatial Distribution of Productivity and the Labor Wedge

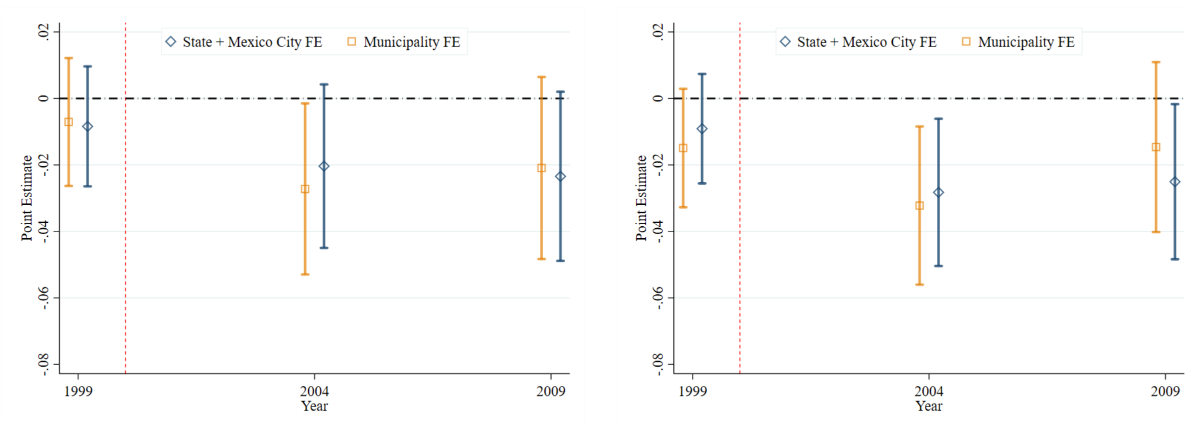


(a) Productivity

(b) Labor wedge

Notes: This figure plots a map of Mexico City with the spatial distribution of productivity measured as value added per worker. I construct ventiles across locations after aggregating value added measures and the total number of workers. Each color represents one of the quantile categories. Census tracts in central areas have higher productivity measures.

Figure B13: Difference in Difference Results-Workers' Informality Share-20 minutes

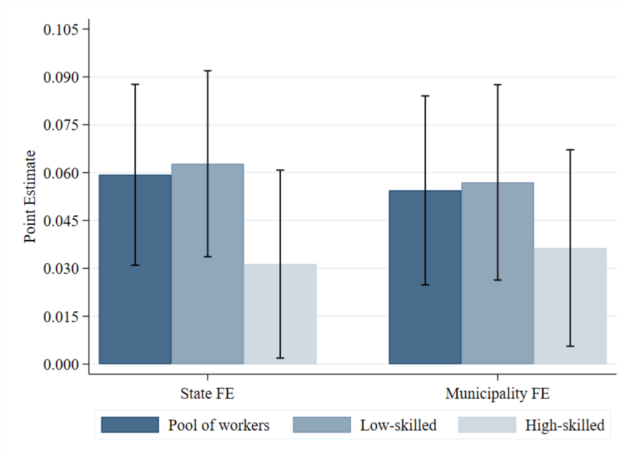


(a) Informal workers

(b) Informal and non-salaried workers

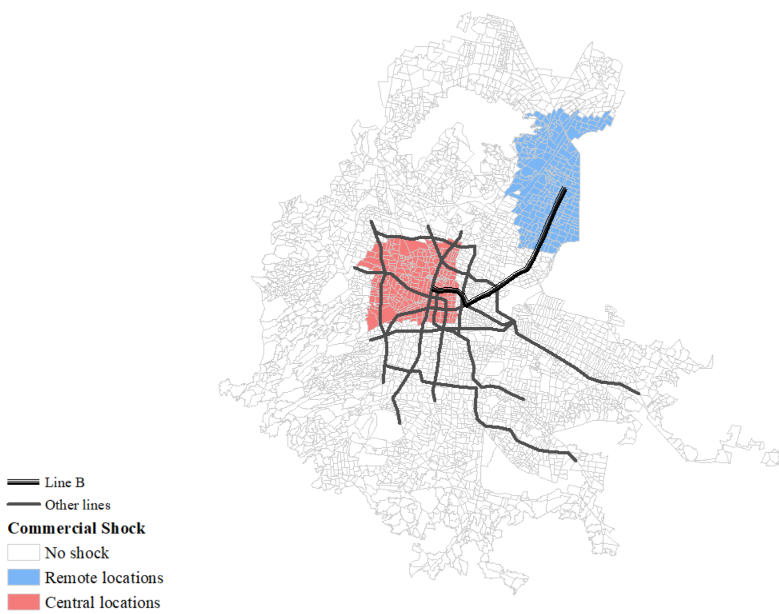
Notes: This figure depicts the point estimates and 90th percentile confidence interval from the difference in difference specification relating workers' informality rates with the transit shock. The treatment group are census tracts with centroids within a walking range of 20 minutes to stations of line B. The control group are census tracts in Mexico City. Panel (a) reports the results for the share of informal workers, and panel (b) for the share of informal and non-salaried workers. Standard errors are clustered at the census tract level.

Figure B14: Difference in Difference Results-Residents' Informality Share-20 minutes



Notes: This figure depicts the point estimate and 90th percentile confidence interval of a regression that relates the change over time in the log of the ratio between formal and informal residents with the transit shock. The treatment variable takes a value of 1 for census tracts with a centroid within a 20 minutes walking range. The first three bars show the results of a regression including distance and population controls with state fixed effects, and the second three bars report the results with municipality fixed effects. Standard errors are clustered at the census tract level.

Figure B15: Place-based policies



Notes: This figure plots a map of Mexico City with the locations in which the Government increases the commercial floorspace for formal firms. The central locations are in red, and the remote locations in blue.

C Additional Tables

Table C1: Informality and Commuting Patterns

	(1)	(2)	(3)	(4)	(5)
	Panel A: Probability of working in the same municipality of residence				
Outcome:	Workplace municipality	Workplace municipality	Workplace municipality	Workplace municipality	Workplace municipality
Informal	-0.265***	-0.231***	-0.231***	-0.132***	-0.079***
	(0.009)	(0.008)	(0.008)	(0.006)	(0.008)
Observations	577,041	577,039	577,039	517,354	516,931
R-squared	0.069	0.098	0.123	0.215	0.465
	Panel B: Probability of working in the CBD of Mexico City				
Outcome:	Workplace-CBD	Workplace-CBD	Workplace-CBD	Workplace-CBD	Workplace-CBD
Informal	-0.086***	-0.056**	-0.059***	-0.037***	-
	(0.026)	(0.024)	(0.018)	(0.011)	-
Observations	577,041	577,039	577,039	517,354	-
R-squared	0.007	0.042	0.468	0.444	-
Individual Characteristics		X	X	X	X
Origin FE			X	X	X
Transportation Mode FE				X	X
Destination FE					X

Notes: This table reports the results of a linear probability model relating the probability of working in the same municipality as the one in which the worker resides, and the probability of working in the CBD with a dummy variable that takes the value of 1 if the worker is informal. Panel A reports the results for working in the same municipality, and panel B whether the individual works in the CBD. Standard errors are clustered at the residence municipality level and reported in parentheses. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table C2: Descriptive Statistics 1999 and 2000

Panel A: Outcomes				
Variable	Mean	Sd	Min	Max
Share informal workers	60.25%	33.37%	0.00%	100.00%
Share informal and non-salaried workers	43.47%	29.60%	0.00%	100.00%
Share informal firms	84.15%	18.26%	0.01%	100.00%
Share informal residents	46.68%	10.58%	1.00%	91.97%
Share informal high-skilled residents	35.65%	7.47%	1.42%	76.99%
Share informal low-skilled residents	50.31%	10.47%	1.07%	93.01%
Panel B: Treatment Variables				
Variable	Mean	Sd	Min	Max
Euclidean Distance to new stations (meters)	11223.33	6625.81	411.89	32838.87
Walking Distance to new stations (minutes)	124.70	73.62	4.58	364.88
Dummy variable (dist<2463)	10.74%	30.97%	0.00%	100.00%
Dummy variable (minutes≤25)	10.00%	30.04%	0.00%	100.00%

Notes: This table reports summary statistic of the main variables. Panel A presents the statistics for the outcomes of interests: workers' informality rates from the Economic Census in 1999 and residents' informality rates from the Population Census in 2000. Panel B for the different definitions of the treatment group that includes: the euclidean distance, the network walking distance, a dummy variable whether the centroid of the ageb is within buffer zone of 2000 meters to the new stations, and a dummy variable whether the centroid of the ageb is within a 25 minutes walking range.

Table C3: Results: Census tract characteristics 1999 and 2000 vs. Treatment

	(1)	(2)	(3)	(4)
Outcome:	ln Income	High Skill Share	Occupation share	Informality Rates
T_i	-0.026***	-0.032***	-0.012***	0.026***
	(0.009)	(0.008)	(0.002)	(0.007)
Observations	3,193	3,193	3,193	3,193
R-squared	0.299	0.205	0.332	0.125
Distance controls	X	X	X	X
State FE	X	X	X	X

Notes: This table reports the results of a regression relating census tract characteristics with a dummy variable whether the centroid of the census tract is within a 25 minutes walking range. The first column reports the results for the log of income, the second column for the share of high-skilled workers, and the third column for the informality rate. Standard errors are clustered at the census tract level and reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C4: Difference-in-Difference - Log individuals

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome:	$\Delta \ln L_i$	$\Delta \ln L_{iF}$	$\Delta \ln L_{iI}$	$\Delta \ln L_i$	$\Delta \ln L_{iF}$	$\Delta \ln L_{iI}$
			Panel A: Pool of workers			
T_i	0.017*	0.057***	-0.010	-0.006	0.030***	-0.034***
	(0.009)	(0.010)	(0.013)	(0.009)	(0.011)	(0.013)
Observations	3,192	3,192	3,192	3,192	3,192	3,192
R-squared	0.310	0.417	0.177	0.365	0.458	0.251
			Panel B: Low-skilled workers			
T_i	0.022***	0.067***	-0.002	-0.001	0.039***	-0.026**
	(0.008)	(0.011)	(0.013)	(0.009)	(0.011)	(0.013)
Observations	3,192	3,192	3,192	3,192	3,192	3,192
R-squared	0.440	0.489	0.220	0.465	0.513	0.280
			Panel C: High-skilled workers			
T_i	0.008	0.022	-0.014	-0.011	0.004	-0.038**
	(0.013)	(0.014)	(0.017)	(0.012)	(0.013)	(0.017)
Observations	3,192	3,192	3,192	3,192	3,192	3,192
R-squared	0.446	0.442	0.375	0.497	0.492	0.427
Controls	X	X	X	X	X	X
State fe	X	X	X			
Municipality fe				X	X	X

Notes: This table reports the results of a regression relating changes in the log of the number of individuals in each location and sector with the line B of the subway. Panel A reports the results for the pool of workers, panel B for low-skilled workers, and panel C for high-skilled workers. In the first three columns, I include state-time fixed effects, and in the fourth column to the sixth column municipality-time fixed effects. The first and fourth column reports the results for the overall number of individuals, the second and fifth column for individuals in the formal sector, and the third and sixth column for workers in the informal sector. The regressions are weighted by the population in 2000. Standard errors are clustered at the census tract level and reported in parentheses. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C5: Difference-in-Difference- Share of Informal Workers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome:	Informal	Informal	Inf.-non salary	Inf.-non salary	Informal	Informal	Inf.-non salary	Inf.-non salary
				Panel A: Continuous Treatment Measure				
-ln distance$_i$ x 1999	0.000	0.002	0.001	0.002	-0.001	0.001	-0.001	-0.000
	(0.004)	(0.005)	(0.004)	(0.004)	(0.006)	(0.006)	(0.005)	(0.006)
-ln distance$_i$ x 1999	-0.008	-0.007	-0.012**	-0.011**	-0.015**	-0.016**	-0.018***	-0.019***
	(0.006)	(0.006)	(0.005)	(0.005)	(0.007)	(0.007)	(0.006)	(0.007)
-ln distance$_i$ x 2004	-0.016***	-0.015**	-0.016***	-0.014**	-0.019**	-0.020**	-0.017**	-0.017**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)	(0.008)	(0.007)	(0.008)
Observations	11,504	11,504	11,504	11,504	11,504	11,504	11,504	11,504
R-squared	0.866	0.866	0.844	0.843	0.869	0.869	0.847	0.847
				Panel B: Treatment Measure using the dummy variable				
T_i x 1999	-0.006	-0.010	-0.001	-0.006	-0.005	-0.010	-0.006	-0.013
	(0.010)	(0.010)	(0.009)	(0.009)	(0.011)	(0.011)	(0.010)	(0.010)
T_i x 2004	-0.023*	-0.026**	-0.023**	-0.029**	-0.033**	-0.036***	-0.028**	-0.035***
	(0.013)	(0.013)	(0.011)	(0.011)	(0.013)	(0.013)	(0.012)	(0.012)
T_i x 2009	-0.036***	-0.035**	-0.034***	-0.036***	-0.037**	-0.036**	-0.026*	-0.029**
	(0.013)	(0.014)	(0.012)	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)
Observations	11,504	11,504	11,504	11,504	11,504	11,504	11,504	11,504
R-squared	0.866	0.866	0.843	0.843	0.869	0.869	0.847	0.847
Mean outcome before the shock	0.582	0.582	0.415	0.415	0.582	0.582	0.415	0.415
Distance Measure	Meters	Minutes	Meters	Minutes	Meters	Minutes	Meters	Minutes
Distance Controls	X	X	X	X	X	X	X	X
State-Time FE	X	X	X	X				
Municipality-Time FE					X	X	X	X

Notes: This table reports the results of a regression relating changes in the share of informal workers in each location with the line B of the subway. Panel A reports the results for the continuous treatment measures, and panel B for the dummy variables. In the first four columns, I include state-time fixed effects, and in the fifth column to the eighth column municipality-time fixed effects. Standard errors are clustered at the census tract level and reported in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table C6: Difference-in-Difference- Share of Informal Firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome:	Informal	Informal	Inf.-non salary	Inf.-non salary	Informal	Informal	Inf.-non salary	Inf.-non salary
Panel A: Continuous Treatment Measure								
-ln distance$_i$ x 1999	-0.005**	-0.005*	-0.004	-0.003	-0.005**	-0.004*	-0.004	-0.003
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
-ln distance$_i$ x 1999	-0.009***	-0.007**	-0.006*	-0.004	-0.009***	-0.009***	-0.006**	-0.005
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
-ln distance$_i$ x 2004	-0.018***	-0.017***	-0.015***	-0.014***	-0.017***	-0.018***	-0.013***	-0.014***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Observations	11,504	11,504	11,504	11,504	11,504	11,504	11,504	11,504
R-squared	0.884	0.883	0.906	0.906	0.892	0.892	0.910	0.910
Panel B: Treatment Measure using the dummy variable								
T_i x 1999	-0.014***	-0.013**	-0.007	-0.006	-0.010**	-0.009*	-0.007	-0.005
	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)
T_i x 2004	-0.022***	-0.020***	-0.015**	-0.013**	-0.017***	-0.015**	-0.014**	-0.012*
	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)
T_i x 2009	-0.032***	-0.029***	-0.022***	-0.019***	-0.026***	-0.023***	-0.019***	-0.016**
	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)
Observations	11,504	11,504	11,504	11,504	11,504	11,504	11,504	11,504
R-squared	0.883	0.883	0.906	0.906	0.892	0.892	0.910	0.910
Mean outcome before the shock	0.833	0.833	0.796	0.796	0.833	0.833	0.796	0.796
Distance Measure	Meters	Minutes	Meters	Minutes	Meters	Minutes	Meters	Minutes
Distance Controls	X	X	X	X	X	X	X	X
State-Time FE	X	X	X	X				
Municipality-Time FE					X	X	X	X

Notes: This table reports the results of a regression relating changes in the share of informal workers in each location with the line B of the subway. Panel A reports the results for the continuous treatment measures, and panel B for the dummy variables. In the first four columns, I include state-time fixed effects, and in the fifth column to the eight column municipality-time fixed effects. Standard errors are clustered at the census tract level and reported in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table C7: Least Cost Path IV- Share of Informal Residents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome:	$\Delta(\ln L_F - \ln L_I)$	$\Delta(\ln L_F - \ln L_I)$	$\Delta(\ln L_F - \ln L_I)$	$\Delta(\ln L_F - \ln L_I)$	$\Delta(\ln L_F - \ln L_I)$	$\Delta(\ln L_F - \ln L_I)$	$\Delta(\ln L_F - \ln L_I)$	$\Delta(\ln L_F - \ln L_I)$
				Panel A: Continuous treatment measure-Pool of residents				
- ln distance	0.047***	0.061***	0.050***	0.065***	0.028***	0.044***	0.030***	0.047***
	(0.008)	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.011)	(0.010)
Observations	3,192	3,192	3,192	3,192	3,192	3,192	3,192	3,192
R-squared	0.074	0.170	0.075	0.170	0.082	0.166	0.083	0.167
				Panel B: Treatment dummy variable-Pool of residents				
T_i	0.076***	0.115***	0.080***	0.121***	0.068***	0.117***	0.072***	0.124***
	(0.021)	(0.021)	(0.022)	(0.023)	(0.025)	(0.023)	(0.026)	(0.025)
Observations	3,192	3,192	3,192	3,192	3,192	3,192	3,192	3,192
R-squared	0.068	0.160	0.067	0.159	0.082	0.165	0.081	0.164
				Panel C: Continuous treatment measure-Low skilled residents				
-ln distance	0.058***	0.065***	0.062***	0.069***	0.033***	0.046***	0.035***	0.049***
	(0.008)	(0.009)	(0.009)	(0.009)	(0.011)	(0.010)	(0.011)	(0.011)
Observations	3,192	3,192	3,192	3,192	3,192	3,192	3,192	3,192
R-squared	0.053	0.154	0.053	0.154	0.065	0.158	0.066	0.158
				Panel D: Treatment dummy variable-Low skilled residents				
T_i	0.100***	0.124***	0.105***	0.130***	0.080***	0.124***	0.085***	0.131***
	(0.023)	(0.022)	(0.024)	(0.024)	(0.027)	(0.025)	(0.028)	(0.026)
Observations	3,192	3,192	3,192	3,192	3,192	3,192	3,192	3,192
R-squared	0.043	0.144	0.042	0.143	0.064	0.156	0.063	0.155
				Panel E: Continuous treatment measure-Outskirt area				
- ln distance	0.080***	0.094***	0.086***	0.100***	0.051***	0.060***	0.054***	0.064***
	(0.010)	(0.010)	(0.011)	(0.011)	(0.012)	(0.010)	(0.013)	(0.011)
Observations	2,171	2,171	2,171	2,171	2,171	2,171	2,171	2,171
R-squared	0.079	0.171	0.080	0.172	0.080	0.155	0.081	0.156
				Panel F: Treatment dummy variable-Outskirt area				
T_i	0.142***	0.217***	0.151***	0.231***	0.129***	0.183***	0.137***	0.195***
	(0.034)	(0.032)	(0.037)	(0.035)	(0.036)	(0.033)	(0.039)	(0.036)
Observations	2,171	2,171	2,171	2,171	2,171	2,171	2,171	2,171
R-squared	0.061	0.150	0.059	0.147	0.076	0.151	0.073	0.147
Distance	Meters	Minutes	Meters	Minutes	Meters	Minutes	Meters	Minutes
Dist.+Prod. Controls	X	X	X	X	X	X	X	X
Population Controls		X		X		X		X
State FE	X	X	X	X				
Municipality FE					X	X	X	X

Notes: This table reports the results of a regression relating changes in the share of informal residents in each location with the line B of the subway using as an instrument the least cost path based on the routes that minimize the cost of building the metro. Panel A reports the results for the continuous treatment measures and the pool of residents, panel B for the treatment dummy variables and the pool of residents, panel C for the continuous treatment measure and low-skilled workers, panel D for the treatment dummy variables and low skilled workers, panel E for the continuous treatment measure on the locations that are not in the CBD, and panel F for the treatment dummy variable on the locations that are not in the CBD. In the first four columns, I include state-time fixed effects, and in the fifth column to the eight column municipality-time fixed effects. The regressions are weighted by the population in 2000. Standard errors are clustered at the census tract level and reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C8: Difference-in-Difference - Different Samples - Share of Informal Residents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Sample crossed by age, gender, and block				Sample that did not change the State in which they were living before			
Outcome:	$\Delta(\ln L_F - \ln L_I)$	$\Delta(\ln L_F - \ln L_I)$	$\Delta(\ln L_F - \ln L_I)$	$\Delta(\ln L_F - \ln L_I)$	$\Delta(\ln L_F - \ln L_I)$	$\Delta(\ln L_F - \ln L_I)$	$\Delta(\ln L_F - \ln L_I)$	$\Delta(\ln L_F - \ln L_I)$
Panel A: Continuous treatment measure-Pool of residents								
- ln distance	0.037***	0.042***	0.019*	0.025**	0.053***	0.056***	0.029***	0.033***
	(0.009)	(0.009)	(0.010)	(0.010)	(0.008)	(0.008)	(0.008)	(0.009)
Observations	1,693	1,693	1,693	1,693	3,193	3,193	3,193	3,193
R squared	0.257	0.258	0.324	0.325	0.250	0.250	0.305	0.305
Panel B: Treatment dummy variable-Pool of residents								
T_i	0.041**	0.034*	0.041**	0.034*	0.066***	0.064***	0.067***	0.063***
	(0.019)	(0.019)	(0.019)	(0.020)	(0.015)	(0.015)	(0.016)	(0.016)
Observations	1,693	1,693	1,693	1,693	3,193	3,193	3,193	3,193
R squared	0.252	0.252	0.324	0.324	0.243	0.243	0.305	0.304
Panel C: Continuous treatment measure-Low skilled residents								
- ln distance	0.040***	0.045***	0.020**	0.026**	0.055***	0.059***	0.031***	0.035***
	(0.009)	(0.009)	(0.010)	(0.010)	(0.008)	(0.008)	(0.008)	(0.009)
Observations	1,693	1,693	1,693	1,693	3,193	3,193	3,193	3,193
R squared	0.258	0.259	0.329	0.330	0.230	0.230	0.283	0.283
Panel D: Treatment dummy variable-Low skilled residents								
T_i	0.044**	0.038*	0.042**	0.036*	0.069***	0.067***	0.068***	0.064***
	(0.019)	(0.020)	(0.020)	(0.020)	(0.016)	(0.016)	(0.016)	(0.017)
Observations	1,693	1,693	1,693	1,693	3,193	3,193	3,193	3,193
R squared	0.253	0.253	0.329	0.329	0.222	0.222	0.283	0.283
Panel E: Continuous treatment measure-Outskirt area								
- ln distance	0.077***	0.085***	0.038***	0.044***	0.090***	0.097***	0.050***	0.055***
	(0.012)	(0.014)	(0.012)	(0.013)	(0.009)	(0.010)	(0.009)	(0.010)
Observations	1,118	1,118	1,118	1,118	2,171	2,171	2,171	2,171
R squared	0.286	0.287	0.348	0.349	0.277	0.277	0.337	0.338
Panel F: Treatment dummy variable-Outskirt area								
T_i	0.132***	0.126***	0.101***	0.092***	0.143***	0.135***	0.112***	0.101***
	(0.025)	(0.026)	(0.027)	(0.028)	(0.019)	(0.020)	(0.021)	(0.022)
Observations	1,118	1,118	1,118	1,118	2,171	2,171	2,171	2,171
R squared	0.275	0.274	0.349	0.348	0.262	0.260	0.336	0.335
Distance	Meters	Minutes	Meters	Minutes	Meters	Minutes	Meters	Minutes
Dist.+Prod. Controls	X	X	X	X	X	X	X	X
Population Controls	X	X	X	X	X	X	X	X
State FE	X	X			X	X		
Municipality FE			X	X			X	X

Notes: This table reports the results of a regression relating changes in the share of informal residents in each location with the line B of the subway for different samples. The first four columns report the results for the sample that I crossed by age, gender, and block. The idea is to compare similar individuals over time. The other four columns report the results for the sample that did not change the State in which they were living before. This is a good proxy to control for migration from the CBD since the central locations are in Mexico City, while the outskirt locations in the State of Mexico. Panel A reports the results for the continuous treatment measures and the pool of residents, panel B for the treatment dummy variables and the pool of residents, panel C for the continuous treatment measure and low-skilled workers, panel D for the treatment dummy variables and low skilled workers, panel E for the continuous treatment measure on the locations that are not in the CBD, and panel F for the treatment dummy variable on the locations that are not in the CBD. In all regressions, I include the population controls. The regressions are weighted by the population in 2000. Standard errors are clustered at the census tract level and reported in parentheses. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table C9: Migration patterns across states using retrospective questions

VARIABLES	(1) Change State	(2) Change State	(3) Change State	(4) Change State	(5) Change State	(6) Change State	(7) Change State	(8) Change State
				Panel A: Continuous Treatment Measure				
$-\ln \text{distance}$	-0.0009	0.0038***	-0.0007	0.0008	-0.0010	0.0043***	-0.0012	0.0010
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$-\ln \text{distance} \cdot \text{formal}_{\omega i}$	0.0017	0.0024**	0.0014	0.0019	0.0030**	0.0039***	0.0024*	0.0031***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.0692***	-1.3933***	0.0392***	-1.2443***	0.0728***	-1.5009***	0.0230**	-1.3176***
	(0.006)	(0.280)	(0.012)	(0.292)	(0.007)	(0.262)	(0.011)	(0.282)
Observations	9,697,144	9,697,144	9,697,144	9,697,144	5,466,452	5,466,452	5,466,452	5,466,452
R-squared	0.001	0.011	0.008	0.013	0.002	0.012	0.009	0.015
				Panel B: Treatment Dummy Variable				
T_i	-0.0005	0.0078***	-0.0005	0.0027	-0.0019	0.0075***	-0.0020	0.0020
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$T_i \cdot \text{formal}_{\omega i}$	0.0010	0.0028	0.0018	0.0024	0.0042	0.0065	0.0051	0.0061
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)
Observations	9,697,144	9,697,144	9,697,144	9,697,144	5,466,452	5,466,452	5,466,452	5,466,452
R-squared	0.001	0.011	0.008	0.013	0.002	0.012	0.009	0.015
Mun FE	-	-	X	X	-	-	X	X
Pop controls	-	X	-	X	-	X	-	X

Notes: This table reports the results of a regression relating changes in the state of residency for each worker with the line B of the subway. Panel A reports the results for the continuous treatment measure, and panel B for the treatment dummy variable. The first four columns show the results for the working age population and the last four columns restrict the sample only for workers. Columns (3), (4), (7), and (8) include municipality fixed effects. Overall, the results suggest very similar mobility patterns between the treated and control locations, and not differential effect between formal and informal workers. Standard errors are clustered at the census tract level and reported in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table C10: Nested Logit - Iceberg Costs

	(1)	(2)	(3)	(4)
Costs:	*Commuting: Trips to work*		*Trade: Trips to shops*	
	Formal	Informal	Formal	Informal
time in minutes	-0.0090***	-0.0082***	-0.0114***	-0.0110***
	(0.0007)	(0.0007)	(0.0004)	(0.0002)
Bus	-0.3984***	-0.3839***	-0.9101***	-1.0551***
	(0.0897)	(0.0066)	(0.1320)	(0.0932)
Metro	-0.6895***	-0.6089***	-1.0520***	-1.2498***
	(0.1257)	(0.1070)	(0.1685)	(0.1244)
Metrobus	-0.4097***	-0.2918***	0.1050	0.3235***
	(0.1128)	(0.0683)	(0.0737)	(0.0472)
Car	-0.3250**	-1.1319***	-1.2788***	-0.6687***
	(0.1020)	(0.1195)	(0.1247)	(0.0697)
lambda public	0.4269***	0.2802***	0.4859***	0.5243***
	(0.0330)	(0.0256)	(0.0165)	(0.0114)
Observations	48,375	28,210	128,245	387,370
Trips	9,675	5,642	25,649	77,474

Notes: This table reports the results of a nested logit using the 2017 OD survey considering only trips that use one transportation mode. The first column reports the results to estimate commuting costs considering only trips from work to home or viceversa between 6am to 10am, and between 5pm to 9pm. The second column reports the results to estimate trade costs using trips to retail shops, outlets, and restaurants. I restrict the sample to trips after 1pm.

D Data and Quantification Appendix

D.1 Nested Logit Estimation

The estimation to transform travel times to iceberg costs is based on the following choice model. A worker ω is choosing between different transportation modes to travel from n to i in sector s. These transportation modes are grouped into different nests, for example public or private nests denoted by $\mathcal{G}$. Denote the set of transportation modes in g, by Υ_g. The indirect utility of choosing transportation model $m \in \Upsilon_g \subset \mathcal{G}$ is:

$$V_{nim\omega} = \delta_s \text{time}_{nim} + \gamma_m + \psi_{nig\omega} + (1 - \lambda_g)\epsilon_{nim\omega},$$

where $V_{nim\omega}$ is the indirect utility of worker ω if he/she chooses transportation mode m to travel from n to i. The parameter δ_s measures the sensitivity of the decision of the worker/consumer to the average time of moving across locations. The parameter γ_m captures preferences for transportation mode m relative to a baseline mode; in my case, I normalize γ_{bus} to zero. The variable ψ is common to all transportation modes for worker/consumer ω within group g and has a distribution function that depends on $\lambda \in (0, 1)$. This latter parameter measures the correlation of errors within each nest. If this parameter is zero we are in the standard multinomial logit case. Finally, $\epsilon_{nim\omega}$ is an idiosyncratic shock to worker ω of choosing m. The is $\psi_{nig\omega} + (1 - \lambda_g)\epsilon_{nim\omega}$ which is drawn from an extreme value-type I distribution.

D.2 Calibration of Speeds

This section describes the calibration of speeds across different transportation modes. I use different sources of information. For the transportation network in Mexico City, I use data from the Government of the city.[44] For the network of roads, I use information from the New York University digital archive in which they report different types of roads for each census tract in the commuting zone of Mexico City. The different roads include: autopistas, calles, viaductos, etc. I calibrate an average speed for each one of the roads. With this information I compute commuting times across census tracts in Mexico City using the Network analysis toolkit from Arcmap (Tsivanidis, 2021). I compute these times for four different modes of transportation: walking, car, traditional buses, and the subway. I add five minutes in each station when I compute times for the public transit network, and three minutes when I compute travel times for "car" to capture the time spent in the parking lot. To compute commuting and shopping iceberg costs, I take an average of these times across the different modes. I calculate a matrix across census tracts of approximately 13 million observations.

Table D11: Calibration of speeds using trip data from Google Maps

Type	Speed
Panel A: Public transit system	
Subway Lines	601.24 m/min
Metrobus	308.13 m/min
Bus	216.67 m/min
Walking	90.00 m/min
Panel B: Types of roads for cars	
Autopista	752.03 m/min
Avenida	266.84 m/min
Boulevard	608.12 m/min
Calle	198.56 m/min
Callejón	69.643 m/min
Calzada	169.98 m/min
Carretera	623.38 m/min
Cerrada	123.39 m/min
Circuito	304.69 m/min
Corredor	160.75 m/min
Eje vial	273.98 m/min
Pasaje	240.71 m/min
Periférico	673.43 m/min
Viaducto	399.99 m/min

Notes: This table reports the calibration of speeds using trips from Google maps. The calibration uses 4,000 random trips. The information was downloaded with the command *gmapsdistance* in R that uses the Distance Matrix Api from Google. I computed these times between 8 am - 11 am and 5 pm - 8 pm under different traffic scenarios.

To calibrate speeds for each mode and each type of road, I use random trips from Google Maps.[45]

[44]The data can be found here.

[45]I did not calculate times across census tracts using Google Maps because the network analysis toolkit is much faster, and the command gmaps distance takes a lot of time.

I downloaded 4000 random trips between 8 am-11 am, and 5 pm-8 pm using the command *gmaps* distance in R that uses the Google Maps Distance Matrix Api. I use as an origin and destination, the closest vertex of each type of road or metro line. This tool has the feature that you can calculate times for different modes under several traffic scenarios: pessimistic, optimistic, or none and modes such as: walking, car, or the public transit network. Using this information, I calibrate speeds for each road and each line using the average time spent to move from one vertex to the other. Table D11 reports the average speed for each one of the roads and the public transit system.

D.3 Calibration of Fixed Costs

Table D12: Estimation of fixed costs

	(1)	(2)	(3)	(4)
Outcome:	ln M_{is}	ln M_{is}	ln M_{is}	ln M_{is}
ln L_{is}	0.715***	0.879***	0.642***	0.568***
	(0.014)	(0.077)	(0.017)	(0.054)
γ_i	1.799***	1.735***	1.825***	1.853***
	(0.034)	(0.036)	(0.051)	(0.046)
ln $w_{is}L_{is}$		-0.154**		0.070
		(0.069)		(0.051)
γ	-1.005***	-0.559***	-0.598***	-0.810***
	(0.055)	(0.194)	(0.091)	(0.183)
Observations	5,387	5,387	4,374	4,374
Adjusted R-squared	0.851	0.853	0.901	0.902
Implied F_I	0.182	0.123	0.117	0.141
Implied F_F	1.366	0.875	0.911	1.124
State FE	X	X		
Municipality FE			X	X

Notes: This table reports the results of a regression relating the number of firms to the number of workers to recover the parameter β and the fixed costs F_I and F_F for the informal and formal sector respectively. The unit of observation is a sector-census-tract cell. The dependent variable is the log number of firms in each cell. Columns 1 and 2 include state fixed effects, while column 3 and 4 include census-tract fixed effects to control for the price of commercial floor space q_i. Even columns add as a control the wage bill for each sector to control for the price per unit of commercial floor space. Standard errors are clustered at the municipality level and reported in parentheses. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

In the model from section 4, in equilibrium, the optimal number of firms is

$$M_{is} = \tilde{\beta} F_s^{-1} \sigma_s^{-1} \tilde{L}_{is}^{\beta} \tilde{Z}_{is}^{\beta}$$

where $\tilde{L}_{is}$ and $\tilde{Z}_{is}$ is the amount of labor and commercial floor-space units employed by location i and sector s, σ_s is the elasticity of substitution, and F_s is the entry fixed cost. Taking logs, I estimate the following equation relating the number of firms to the number of workers for both sectors in the baseline year. This estimation allows me to recover the parameters F_s:

$$\ln M_{is} = \beta \ln L_{is} + (1-\beta) \underbrace{\ln Z_{is}}_{\frac{w_{is}L_{is}}{q_i}} - \underbrace{\ln \sigma_s - \ln F_s}_{\gamma_s}. \tag{D.1}$$

In some of my specifications, to control for Z_{is}, I include the wage bill for each sector and location with a census-tract fixed effect to capture q_i. Then, I estimate the following equation using the Economic Censuses in 1999, the omitted category is the formal sector,

$$\ln M_{is} = \underbrace{\gamma_1}_{\beta} \ln L_{is} + \underbrace{\gamma_2}_{1-\beta} \ln w_{is}L_{is} + \gamma_i + \gamma_I + \gamma + \epsilon_{is}, \tag{D.2}$$

where γ_i is the census-tract fixed effect, γ_I is an informal sector dummy variable, and γ is a constant term. From the optimal number of firms, we have that $\gamma_I = \ln(\sigma_I F_I)$, and $\gamma = \ln \tilde{\beta} + \ln(\sigma_F F_F)$.

Table D12 reports the results for this estimation for different specifications. I run the previous equation, including state and municipality fixed effects, and in the even columns, I control for the wage bill. I obtained that on average, the value of $\beta \approx 0.7$. I also find that the entry fixed cost for a firm into the informal sector is approximately 0.15, and into the formal sector is 1.1. This means that the fixed cost to enter into the formal sector is more than five times the one to enter into the informal sector. This result is consistent with the fact that the average size in terms of workers of informal firms is lower, but that there are more informal firms in the economy.

D.4 Algorithm

In this section, I explain the main algorithm to solve for the general equilibrium model. The system of equations is described in section 4. The sub-index t represents simulation. The algorithm is based on Alvarez and Lucas (2007) and it is a contraction mapping. It is as follows:

1. Guess an initial vector of wages $\vec{w}^0$, and number of residents in each location $\vec{L}^0$.
2. Given a vector $\vec{w}^t$ and $\vec{L}^t$, compute the following equations:
   - Labor supply equations:

$$\lambda_{nisL|ns} = \frac{w_{is}^{\theta_s} d_{ni}^{-\theta_s}}{\sum_{i'} w_{i's}^{\theta_s} d_{ni'}^{-\theta_s}} \tag{D.3}$$

$$\lambda_{nsL|n} = \frac{W_{ns|n}^{\kappa}}{\sum_{s'} W_{ns'|n}^{\kappa}}, \quad W_{ns|n}^{\theta_s} = \sum_{i'} w_{is}^{\theta_s} d_{ni}^{-\theta_s} \tag{D.4}$$

$$\tilde{L}_{is} = \sum_n \lambda_{nis} \cdot \bar{L}_L. \tag{D.5}$$

   - Average income

$$\bar{y}_n \equiv \sum_{i,s} \lambda_{nis} w_{is} \tag{D.6}$$

   - Commercial floor space prices

$$q_i \tilde{Z}_i = \sum_s \frac{(1-\beta)(1+t_{isL}) w_{is} \tilde{L}_{is}}{\beta(1+t_{isZ})}, \tag{D.7}$$

- Number of firms

$$M_{is} = \frac{\tilde{\beta}\tilde{L}_{is}^{\beta}\tilde{Z}_{is}^{1-\beta}}{\sigma_s F_s}, \tag{D.8}$$

- Expenditure shares

$$\pi_{nis} = \underbrace{\frac{P_{ns}^{1-\xi}}{\sum_{s'} P_{ns'}^{1-\xi}}}_{\pi_{ns}} \cdot \underbrace{\frac{M_{is} p_{nis}^{1-\sigma}}{\sum_{i'} M_{i's} p_{ni's}^{1-\sigma}}}_{\pi_{nis|s}}, \quad \text{with} \quad P_{ns} = \left(\sum_i M_{is} p_{nis}^{1-\sigma_s}\right)^{\frac{1}{1-\sigma_s}}, \tag{D.9}$$

- Government budget constraint

$$\delta \equiv \frac{\sum_{i,s}\left(t_{isL} w_{is}\tilde{L}_{is} + t_{isZ} q_i \tilde{Z}_{is}\right)}{\sum_n \bar{y}_n L_n + q_n Z_n}$$

$$\bar{t} = \frac{\alpha \cdot \delta}{1 + (1-\alpha)\cdot\delta} \tag{D.10}$$

- Aggregate Expenditure

$$X_n = \frac{(1+\bar{t})}{\alpha - \bar{t}(1-\alpha)}\left(\bar{y}_n L_n + q_n Z_n\right). \tag{D.11}$$

- Labor demand

$$Y_{is} = \alpha \sum_n \pi_{nis} X_n. \tag{D.12}$$

$$LD_{is} = \frac{\alpha\beta Y_{is}}{w_{is}^t} \tag{D.13}$$

- Calculate the difference between labor demand and labor supply and the number of residents

$$z_w = \frac{\alpha\beta Y_{is} - w_{is}^t(1+t_{isL})\tilde{L}_{is}}{w_{is}^t(1+t_{isL})\tilde{L}_{is}} \tag{D.14}$$

$$\tilde{L}_n^t = \left(\frac{B_n P_n^{-\alpha\eta} r_n^{-(1-\alpha)\eta} W_n^{\eta}}{\sum_{n'} B_{n'} P_{n'}^{-\alpha\eta} r_{n'}^{-(1-\alpha)\eta} W_{n'}^{\eta}}\right)\bar{L}_L \tag{D.15}$$

3. If $||(z_w, \tilde{L}_i^t) - (0, L_i^t)|| < \epsilon^{\text{tol}}$ then, the algorithm stops. Otherwise, update

$$w_{is}^{t+1} = w_{is}^t(1+\nu_w z_w) \tag{D.16a}$$
$$L_n^{t+1} = \nu_L \tilde{L}_n^t + (1-\nu_L)L_n^t, \tag{D.16b}$$

where ν_L, and ν_w are convergence parameter and ϵ^{tol} is a tolerance value.

D.5 Additional Infrastructure Counterfactuals

In this section, I report the results of two additional counterfactuals. In the first counterfactual, I assume that the Government only gives the rebate to formal workers instead of the entire population in the city. In the second counterfactual, I compute travel times without Lines 1 and 2 of the subway and show that the resource misallocation component only explains half of the total gains relative to line B.

D.6 Formal workers rebate

I now consider what are the welfare gains of line B under the assumption that the Government only gives the rebate to the formal workers. There are two main equations that change from the general equilibrium framework. First the labor supply equation from the formal sector is now given by:

$$\lambda_{nFL|n} = \frac{B_{nF} W_{nF}^{\kappa} (1+\bar{t})^{\kappa}}{B_{nF} W_{nF}^{\kappa} (1+\bar{t})^{\kappa} + B_{n\mathrm{I}} W_{n\mathrm{I}}^{\kappa}}, \tag{D.17}$$

and the new Government budget constraint that pin downs the value of $\bar{t}$ is given by:

$$\sum_{i,s} \left(t_{isL} w_{is} \tilde{L}_{is} + t_{isZ} q_i \tilde{Z}_{is} \right) = \bar{t} \bar{L} \cdot \sum_{i,n} \lambda_n \lambda_{nFL|n} \lambda_{niFL|nF} w_{iF}. \tag{D.18}$$

We can solve the system of equations with these two new equations. Table D13 reports the results for the counterfactual of line B. Overall, the results are very similar to the baseline simulations. The welfare gains are between 1.7%-1.8%, and the resource misallocation component explains between 15% to 20%.

Table D13: Counterfactual Results $\hat{X} = X'/X$ - Line B

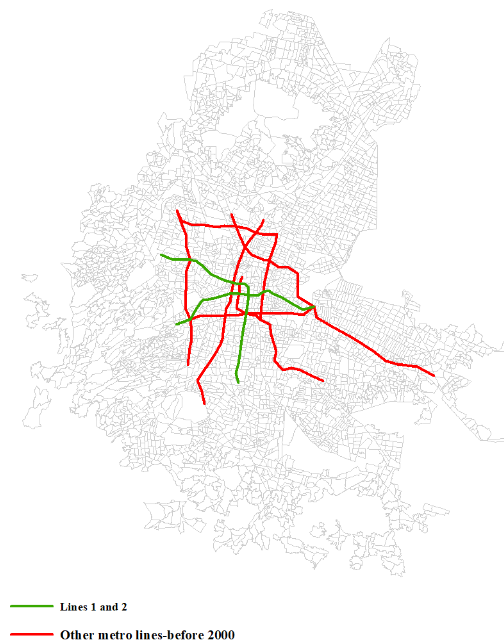
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Percentage change in welfare-Distortions					
		No Migration			Migration	
%Δ Welfare	Δd_{ni}	$\Delta\tau_{ni}$	$\Delta d_{ni}, \Delta\tau_{ni}$	Δd_{ni}	$\Delta\tau_{ni}$	$\Delta d_{ni}, \Delta\tau_{ni}$
Panel A: Calibrated wedges						
Total change	1.00%	0.67%	1.79%	1.01%	0.67%	1.77%
Decomposition						
Pure Effect	87.37%	75.70%	81.98%	83.60%	71.73%	78.32%
Allocation	11.28%	14.51%	13.82%	14.94%	18.35%	17.20%
Agglomeration	1.34%	9.79%	4.21%	1.45%	9.93%	4.48%
	Panel B: Percentage change in welfare-Constant wedge					
%Δ Welfare	Δd_{ni}	$\Delta\tau_{ni}$	$\Delta d_{ni}, \Delta\tau_{ni}$	Δd_{ni}	$\Delta\tau_{ni}$	$\Delta d_{ni}, \Delta\tau_{ni}$
Total change	0.95%	0.64%	1.71%	0.94%	0.63%	1.65%
Decomposition						
Pure Effect	92.13%	78.17%	86.19%	89.69%	76.38%	84.07%
Allocation	7.04%	14.87%	10.94%	9.34%	16.22%	12.70%
Agglomeration	0.83%	6.97%	2.88%	0.97%	7.39%	3.23%

Notes: This table reports the counterfactual results for Line B of the subway with a rebate only to formal workers. The first and fourth column considers only change in commuting costs, the second and fifth column changes in trade costs, and the third and sixth column considers changes in both type of iceberg costs. The first three columns presents the results for the counterfactual with no migration, and the second three columns for the counterfactual in which I allow for migration in the model. Panel A reports the results for welfare with the calibrated distortions a lá Hsieh & Klenow (2009), and panel B for welfare with a constant wedge in the formal sector based on Levy (2018). The first row describes the results considering the total change. While, the other rows decompose the total change into the different components. The second row shows the percentage explained by the direct effect, the third row by the allocative efficiency margin, and the fourth row by the agglomeration externality component.

D.7 Line 1 and 2

This section reports the result of a counterfactual, in which I remove lines 1 and 2 of the subway. These lines have the characteristic of connecting the central areas in the city. Figure D16 plots a map of the city highlighting lines 1 and 2. The interpretation of the counterfactual consists of an allocation without these lines, starting from a world with these lines.

Figure D16: Transit System-Lines 1 and 2



(a) Subway Lines

Notes: This figure plots a map of Mexico City with the transportation system highlighting the first two lines of the subway: lines 1 and 2. In this counterfactual, I remove these lines to measure the effect on informality and welfare

Table D14 reports the main findings. Overall, lines 1 and 2 lead to a real income increase of around 2.7%. However, the allocation component explains a lower fraction of the total gains relative to line B since it only explains 10% of the welfare gains. In contrast, in the case of line B, the reallocation of workers explains more than 20%. Then, Line B generated a larger reallocation of workers from the informal to the formal sector relative to the size of the shock.

Table D14: Counterfactual Results $\hat{X} = X'/X$ - Lines 1 and 2

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Percentage change in welfare-Distortions					
		No Migration			Migration	
%Δ **Welfare**	Δd_{ni}	$\Delta\tau_{ni}$	$\Delta d_{ni}, \Delta\tau_{ni}$	Δd_{ni}	$\Delta\tau_{ni}$	$\Delta d_{ni}, \Delta\tau_{ni}$
Total change	1.57%	1.16%	2.70%	1.56%	1.16%	2.69%
Decomposition						
Pure Effect	96.71%	78.88%	89.27%	96.77%	78.87%	89.30%
Allocation	2.93%	10.02%	5.87%	2.86%	9.80%	5.74%
Agglomeration	0.36%	11.10%	4.86%	0.37%	11.33%	4.96%
	Panel B: Percentage change in welfare-Constant wedge					
%Δ **Welfare**	Δd_{ni}	$\Delta\tau_{ni}$	$\Delta d_{ni}, \Delta\tau_{ni}$	Δd_{ni}	$\Delta\tau_{ni}$	$\Delta d_{ni}, \Delta\tau_{ni}$
Total change	1.56%	1.14%	2.67%	1.56%	1.14%	2.67%
Decomposition						
Pure Effect	96.93%	80.50%	90.11%	96.88%	80.38%	90.05%
Allocation	2.69%	7.25%	4.57%	2.71%	7.15%	4.54%
Agglomeration	0.38%	12.26%	5.32%	0.41%	12.47%	5.41%

Notes: This table reports the counterfactual results for Lines 1 and 2 of the subway. The first and fourth column considers only change in commuting costs, the second and fifth column changes in trade costs, and the third and sixth column considers changes in both type of iceberg costs. The first three columns presents the results for the counterfactual with no migration, and the second three columns for the counterfactual in which I allow for migration in the model. Panel A reports the results for welfare with the calibrated distortions a lá Hsieh & Klenow (2009), and panel B for welfare with a constant wedge in the formal sector based on Levy (2018). The first row describes the results considering the total change. While, the other rows decompose the total change into the different components. The second row shows the percentage explained by the direct effect, the third row by the allocative efficiency margin, and the fourth row by the agglomeration externality component.

E Theoretical Appendix

E.1 Welfare Decomposition

In this section, I derive the formula for the welfare decomposition. I start with the perfectly efficient economy and then, I introduce labor wedges. As in the text, there are three group of agents: workers denoted by L, commercial floor space owners denoted by Z, and house owners denoted by H. The two latter groups do not commute.

The indirect utility of agent ω is:

$$V_{ni\omega} = B_n \frac{d_{ni} w_{is} \epsilon_{ni\omega}}{r_n^{\beta} P_n^{1-\beta}} \tag{E.1}$$

where w_{is} is the wage per efficiency unit in location i, and sector s, and $\epsilon_{ni\omega}$ is an idiosyncratic shock drawn from a nested Fréchet distribution with dispersion parameters θ_s, and κ. By the properties of the Fréchet, the total amount of efficiency units $d_{ni}^{-1}\tilde{L}_{nis}$ net of commuting costs provided by location n to location i-sector s is:

$$w_{is} d_{ni}^{-1} \tilde{L}_{nis} = \lambda_n \lambda_{ns|n} \lambda_{nis|ns} \bar{y}_n \bar{L}, \tag{E.2}$$

where $\bar{y}_n \equiv \left(\sum_s B_{ns} W_{ns}^{\kappa}\right)^{\frac{1}{\kappa}}$, and $W_{ns} \equiv \left(\sum_i w_{is}^{\theta_s} d_{ni}^{-\theta_s}\right)^{\frac{1}{\theta_s}}$. From these expressions, the goods market clearing condition is the following system of equations:

$$\lambda_n\lambda_{ns|n}\lambda_{nis|ns}\bar{y}_n\bar{L} = \alpha\beta\sum_n \pi_{ns}\pi_{nis|s}\left(\bar{y}_n\lambda_n\bar{L} + q_n\lambda_{nZ}Z + r_n\lambda_{nH}H\right) \tag{E.3a}$$

$$q_n\lambda_{nZ} = \alpha(1-\beta)\sum_n \pi_{ns}\pi_{nis|s}\left(\bar{y}_n\lambda_n\bar{L} + q_n\lambda_{nZ}Z + r_n\lambda_{nH}H\right). \tag{E.3b}$$

And the housing market clearing condition is:

$$r_n\lambda_{nH}H = (1-\alpha)\left(\bar{y}_n\lambda_n\bar{L} + q_n\lambda_{nZ}Z + r_n\lambda_{nH}H\right) \tag{E.3c}$$

And the average utility in each location is:

$$\bar{U}_n = \frac{B_n\bar{y}_n}{P_n^{\alpha}r_n^{1-\alpha}} \tag{E.4}$$

E.1.1 Social Planner

There is a social planner maximizing welfare such that the market allocation replicates the perfectly efficient allocation. The problem of the planner consists to maximize:

$$\bar{U} = \omega_L\underbrace{\sum_n \delta_n\bar{U}_n}_{\bar{U}_L} + \omega_Z\underbrace{\sum_n \delta_{nZ}\bar{U}_{nZ}}_{\bar{U}_Z} + \omega_H\underbrace{\sum_n \delta_{nH}\bar{U}_{nH}}_{\bar{U}_H}, \tag{E.5}$$

where ω and δ are weights that replicate the market allocation.[46] As shown later $\frac{\omega_L\bar{U}_L}{\bar{U}} = \alpha\beta$. I am interested in a shock to commuting costs or trade costs. Then, by a first-order approximation, the effect of any shock is:

$$d\ln\bar{U} = \alpha\beta\sum_n \tilde{\lambda}_{nL}\left(d\ln\bar{y}_n - \alpha d\ln P_n - (1-\alpha)d\ln r_n\right) \tag{E.6a}$$

$$+\,\alpha(1-\beta)\sum_n \tilde{\lambda}_{nZ}\left(d\ln q_n - \alpha d\ln P_n - (1-\alpha)d\ln r_n\right) \tag{E.6b}$$

$$+\,(1-\alpha)\sum_n \tilde{\lambda}_{nH}\left(d\ln r_n - \alpha d\ln P_n - (1-\alpha)d\ln r_n\right), \tag{E.6c}$$

where $\tilde{\lambda}_{nL} \equiv \frac{\bar{y}_n\lambda_n}{\sum_{n'}\bar{y}_{n'}\lambda_{n'}}$ is the share of total labor income in location n, and similarly, $\tilde{\lambda}_{nZ}$ ($\tilde{\lambda}_{nH}$) is the share of total income of commercial floor space (housing) in location n. Then, the change in the average income, and the price index is:

$$d\ln W_n = \sum_{i,s}\lambda_{ns|n}\lambda_{nis|ns}d\ln w_{is} - \sum_{i,s}\lambda_{ns|n}\lambda_{nis|ns}d\ln d_{ni} \tag{E.7a}$$

$$d\ln P_n = \sum_{i,s}\pi_{ns}\pi_{nis|s}(\beta d\ln w_{is} + (1-\beta)d\ln q_i) + \sum_{i,s}\pi_{ns}\pi_{nis|s}d\ln\tau_{ni}. \tag{E.7b}$$

[46] To replicate the market allocation, $\bar{U} = \sum_n \bar{y}_n L_n + q_n Z_n + r_n H_n$

From the goods market clearing condition and with some algebra manipulation then:

$$d\ln \bar{U} = -\alpha\beta \sum_{n,s,i} \left(\tilde{\lambda}_{nL}\lambda_{ns|n}\lambda_{nis|ns}\right) d\ln d_{ni} \tag{E.8a}$$

$$- \alpha \sum_{n,s,i} \pi_{ns}\pi_{nis|s} \left(\alpha\beta\tilde{\lambda}_{nL} + \alpha(1-\beta)\tilde{\lambda}_{nZ} + (1-\alpha)\tilde{\lambda}_{nH}\right) d\ln \tau_{ni}. \tag{E.8b}$$

This equation is the Hulten result. When the economy is perfectly efficient, the change in welfare is a weighted average of the change in the fundamentals. In this case, changes in trade and commuting costs.

E.1.2 Labor wedge

I now assume that firms face distortions. These wedges can be variable markups or taxes. As in HK, I am going to denote these wedges as taxes. In particular, the goods market clearing condition now is:

$$\lambda_n\lambda_{ns|n}\lambda_{nis|ns}\bar{y}_n\bar{L} = \frac{1+\bar{t}}{1+t_{isL}}\alpha\beta \sum_{n} \pi_{ns}\pi_{nis|s} \left(\bar{y}_n\lambda_n\bar{L} + q_n\lambda_{nZ}Z + r_n\lambda_{nH}H\right), \tag{E.9}$$

where $1+\bar{t}$ is a rebate of the Government that can vary by location, or in the case of markups a portfolio that is rebate to households. The previous equation create trade imbalances and wedges across firms. Thus, there is an additional effect in the first-order approximation. This effect captures changes in wages and it is:

$$d\ln \bar{U} = -\alpha\beta \sum_{n,s,i} \left(\tilde{\lambda}_{nL}\lambda_{ns|n}\lambda_{nis|ns}\right) d\ln d_{ni} \tag{E.10a}$$

$$- \alpha \sum_{n,s,i} \pi_{ns}\pi_{nis|s} \left(\alpha\beta\tilde{\lambda}_{nL} + \alpha(1-\beta)\tilde{\lambda}_{nZ} + (1-\alpha)\tilde{\lambda}_{nH}\right) d\ln \tau_{ni} \tag{E.10b}$$

$$+ \alpha\beta \sum_{n,i,s} \tilde{\lambda}_{nL}\lambda_{ns|n}\lambda_{nis|ns} \left(\frac{t_{isL}-\bar{t}}{1+\bar{t}}\right) d\ln w_{is} \tag{E.10c}$$

$$+ d\ln(1+\bar{t}). \tag{E.10d}$$

It is easy to show that the change in the rebate is:

$$d\ln(1+\bar{t}) = \sum_{n,i,s} \tilde{\lambda}_{nL}\lambda_{ns|n}\lambda_{nis|ns} \left(\frac{t_{isL}-\bar{t}}{1+\bar{t}}\right) (d\ln w_{is} + d\ln \tilde{L}_{nis}).$$

Then, the total change in welfare is:

$$d\ln\bar{U} = -\alpha\beta\sum_{n,s,i}\left(\tilde{\lambda}_{nL}\lambda_{ns|n}\lambda_{nis|ns}\right)d\ln d_{ni} \tag{E.11a}$$

$$-\alpha\sum_{n,s,i}\pi_{ns}\pi_{nis|s}\left(\alpha\beta\tilde{\lambda}_{nL}+\alpha(1-\beta)\tilde{\lambda}_{nZ}+(1-\alpha)\tilde{\lambda}_{nH}\right)d\ln\tau_{ni} \tag{E.11b}$$

$$+\alpha\beta\sum_{n,i,s}\tilde{\lambda}_{nL}\lambda_{ns|n}\lambda_{nis|ns}\left(\frac{t_{isL}-\bar{t}}{1+\bar{t}}\right)d\ln\tilde{L}_{nis}. \tag{E.11c}$$

The third term captures agglomeration forces and it suggests that when workers reallocate to sectors-locations with larger wedges, there is an additional increase in welfare due to an improvement in allocative efficiency.

E.1.3 Agglomeration forces

Finally, there is an additional effect due to agglomeration forces. In my model this force comes from LOV. This additional effect also captures changes in allocative efficiency and it arises for two reasons. First, if agglomeration externalities differ between the two sectors as in BCDR, or because there are trade imbalances as in FG. In the presence of LOV or agglomeration forces, consumers benefit from lower prices as the sector-location becomes bigger. In particular, there is an additional change in welfare captured by:

$$d\ln\bar{U} = ... + \frac{\beta}{1+\sigma_s}\sum_{n,i,s}\pi_{ns}\pi_{nis|s}\left(\alpha\beta\tilde{\lambda}_{nL}+\alpha(1-\beta)\tilde{\lambda}_{nZ}+(1-\alpha)\tilde{\lambda}_{nH}\right)d\ln\tilde{\lambda}_{is}$$

$$d\ln\bar{U} = ... + \frac{\beta}{1+\sigma_s}\sum_{n,i,s}\left(\frac{1+t_{isL}}{1+\bar{t}}\right)d\tilde{\lambda}_{is}, \tag{E.12}$$

where $\tilde{\lambda}_{is}$ is the labor share in total income from sector s and location i. This additional term captures two things. First, if workers move to sectors-location in which agglomeration externalities are larger, then there is an increase in total welfare, and second, if workers reallocate to sectors-location with larger wedges the effect of any shock on welfare is larger.

Combining the previous expressions, then,

$$d\ln\bar{U} = \underbrace{-\alpha\beta\sum_{n,i,s}\left(\tilde{\lambda}_{nL}\lambda_{ns|n}\lambda_{nis|ns}\right)\cdot d\ln d_{ni}}_{\text{“Pure” effect commuting costs}} \tag{E.13a}$$

$$\underbrace{-\alpha\sum_{n,i,s}\pi_{ns}\pi_{nis|s}\left(\alpha\beta\tilde{\lambda}_{nL}+\alpha(1-\beta)\tilde{\lambda}_{nZ}+(1-\alpha)\tilde{\lambda}_{nH}\right)d\ln\tau_{ni}}_{\text{“Pure” effect trade costs}} \tag{E.13b}$$

$$\underbrace{+\alpha\beta\left(\sum_{n,i,s}\tilde{\lambda}_{nL}\lambda_{ns|n}\lambda_{nis|ns}\left(\frac{t_{isL}-\bar{t}}{1+\bar{t}}\right)d\ln\tilde{L}_{nis}\right)}_{\text{Allocative efficiency}} \tag{E.13c}$$

$$\underbrace{+\sum_{n,i,s}\frac{1}{\sigma_s-1}\sum_{g}\beta_g\left(\frac{1+t_{isg}}{1+\bar{t}}\right)d\tilde{\lambda}_{isg},}_{\text{Agglomeration Forces}} \tag{E.13d}$$

which is the same expression as in the text.

E.2 The problem of the social planner

In this section, I find the equilibrium conditions for the problem of the social planner. I show two results. First, in the case in which the economy operates under perfect competition, the market allocation coincides with the efficient allocation. Second, the variable $\bar{U}$ is equal to the aggregate total expenditure or income of the economy, which is the main assumption from the previous section.

There are different groups of workers indexed by g, sectors indexed by s and a mass of locations $\mathcal{N}$ indexed by n and i. Each group has a utility function $U_g(c_{ng}, h_{ng})$, where c_{ng} represents the average consumption of a composite good in location n and h_{ng} is the average amount of housing in location n. This utility function is homogeneous of degree one. In the optimal allocation, workers are indifferent across locations and there are iceberg trade and commuting costs. The problem of the planner is to maximize the following welfare function:

$$\bar{U} = \lambda_g \cdot U_g$$

subject to *i)* spatial mobility constraints

$$U_{ng}L_{ng} \leq \bar{U}_g \ \ \forall n, g$$

ii) composite and housing feasibility constraints

$$\sum_{n,s}\tau_{ni}Q_{is} \leq Y_{is}(E_{gis}) \ \ \forall i, s$$

$$L_{ng}\cdot c_{ng} \leq C(Q_{n11g}, ..., Q_{nSNg}) \ \ \forall n$$

$$L_{ng}\cdot h_{ng} \leq H_n(\tilde{E}_{nhg}) \ \ \forall n$$

iii) labor supply constraints

$$\tilde{E}_{isg} \leq \sum_n d_{ni}^{-1} E_{nisg} \;\; \forall i, s, g \text{ including the sector that produces housing}$$

$$E_g(E_{n11g}, ..., E_{nSNg}) \leq L_{n,g} \;\; \forall n, g$$

iv) non-negativity constraints of commuting flows, trade flows, labor.
v) Labor Market clearing

$$\sum_{n,g} L_{n,g} \leq \bar{L}_g$$

where Y is the production function, $C(\cdot)$ is a composite good aggregator across locations and sectors, in my case the nested CES; $E(\cdot)$ is a efficiency units aggregator, in my case the nested Fréchet; and E_{nisg} are efficiency units provided from location n to i, s by group g.[47] The other parameters represent the same variables as in section 4.

The Lagrangian of the planning problem omitting the non-negative constraints is:

$$\begin{aligned}
\mathcal{L} = L_g U_g &- \sum_{n,g} \omega_{ng} L_{ng} \left(U_g - U_g(c_{ng}, h_{ng})\right) \\
&- \sum_{i,s} p_{is}^* \left(\sum_n \tau_{ni} Q_{nis} - Y_{is}(\tilde{E}_{isg}) \right) \\
&- \sum_n P_n^* \left(\sum_g L_{ng} c_{ng} - C(Q(Q_{n11g}, ..., Q_{nSNg})) \right) \\
&- \sum_{i,s,g} w_{isg}^* \left(\tilde{E}_{isg} - \sum_n d_{ni}^{-1} E_{nisg} \right) \\
&- \sum_{n,g} \bar{y}_{n,g}^* \left(E_g(E_{n11g}, ..., E_{nSNg}) - L_{n,g} \right) \\
&- \sum_n r_n^* \left(\sum_g L_{ng} h_{ng} - H_n(\tilde{E}_{nhg}) \right) \\
&- \sum_g \Psi_g (\sum_n L_{ng} - \bar{L}_g) + ...
\end{aligned}$$

The planner chooses c_{ng}, h_{ng}, Q_{nis}, E_{nisg}, $\tilde{E}_{isg}$, $\tilde{E}_{ihg}$, L_{ng}, and U_g to maximize welfare. I proceed in two parts. First, I show the relationship between $\bar{U}$ and aggregate expenditure, and then, I show that the market allocation coincides with the efficient allocation. Then, I generalized the formula from the previous section using the goods market clearing condition.

Utility and Total Expenditure

The F.O.C with respect to c_{ng} and h_{ng} is:

$$\omega_{ng} c_{ng} \frac{\partial U_g}{\partial c} \leq P_n^* c_{ng} \quad \forall g$$

[47] Recall that the CES aggregator from section 4 is $C_n^{\frac{\xi-1}{\xi}} \equiv \sum_s Q_{ns}^{\frac{\xi-1}{\xi}}$, where $Q_{ns}^{\frac{\sigma_s-1}{\sigma_s}} \equiv \sum_i Q_{nis}^{\frac{\sigma_s-1}{\sigma_s}}$ and the efficiency units aggregator is $E_n^{\frac{\kappa}{\kappa-1}} \equiv \sum_s E_{ns}^{\frac{\kappa}{\kappa-1}}$, where $E_{ns}^{\frac{\theta_s}{\theta_s-1}} = \sum_i E_{nis}^{\frac{\theta_s}{\theta_s-1}}$.

$$\omega_{ng} h_{ng} \frac{\partial U_g}{\partial h} \leq r_n^* h_{ng} \quad \forall g$$

Since $U_g(\cdot)$ is homogeneous of degree one, then,

$$L_{ng} \left(P_n^* c_{ng} + r_n^* h_{ng} \right) = L_{ng} \omega_{ng} U_{ng} \tag{E.14}$$

The LHS of equation E.14 is the aggregate expenditure X_{ng} of group g who lives in location n. The F.O.C whit respect to U_g is:

$$\sum_n \omega_{ng} L_{ng} = L_g$$

Combining this equation with equation E.14, and the fact that in equilibrium $U_{ng} = U_g$ for all the locations in which $L_{ng} > 0$ yield that:

$$L_g U_g = \sum_n X_{ng}$$

Recall that $\bar{U} = \sum_g L_g U_g$, thus,

$$\bar{U} = X$$

where $X \equiv \sum_{n,g} X_{ng}$ is aggregate expenditure. At the aggregate level, total expenditure is equal to total income then in the previous section $\bar{U} = \sum_n \bar{y}_n L_n + q_n \tilde{Z}_n + r_n H_n$, which was the assumption for the theoretical result of the first-order approximation.

Efficient Allocation

Now, I show that the market allocation coincides with the efficient allocation. The F.O.C with respect to other variables is:

$$[Q_{nis}] : P_n^* \frac{\partial C}{\partial Q_{nis}} \leq p_{is}^* \tau_{ni} \tag{E.15a}$$

$$[\tilde{E}_{isg}] : p_{is}^* \frac{\partial Y}{\partial \tilde{E}_{isg}} \leq w_{isg}^* \tag{E.15b}$$

$$[E_{nisg}] : w_{isg}^* d_{ni}^{-1} \leq \bar{y}_{ng} \frac{\partial E_g}{\partial E_{nisg}} \tag{E.15c}$$

$$[\tilde{E}_{nhg}] : r_n^* \frac{\partial H}{\partial \tilde{E}_{nhg}} \leq w_{nhg} \tag{E.15d}$$

$$[L_{ng}] : \bar{y}_n \leq \Psi_g \tag{E.15e}$$

Equations E.15a to E.15d are the same as the utility and profit maximization conditions of the consumer's and firm's problem. In the particular case in which the function $C(\cdot)$ is the nested CES utility function from section 4, $E(\cdot)$ is the nested Frechet, and assuming that $Y(\cdot)$ is homogeneous of degree one, I can rewrite these conditions as:

$$\lambda_{nsg|n} \lambda_{nisg|ns} \bar{y}_{ng}^* L_{ng} = w_{isg}^* d_{ni}^{-1} E_{nisg}$$

$$w_{isg}^* \tilde{E}_{isg} = \beta_{isg} p_{is}^* Y_{is}$$

$$p_{is}^{*}Y_{is}=\sum_{n,g}\alpha_{ng}\pi_{nis}\bar{y}_{ng}^{*}L_{ng}$$

$$r_{n}^{*}H_{n}=\sum_{n,g}(1-\alpha_{ng})\bar{y}_{ng}^{*}L_{ng},$$

where

$$\beta_{isg}\equiv\frac{E_{isg}\frac{\partial Y}{\partial E_{isg}}}{Y_{is}}$$

$$\alpha_{ng}\equiv\frac{c_{ng}\frac{\partial U_g}{\partial c_{ng}}}{U_{ng}}$$

These are the same conditions as the market allocation from the previous section. Then, the market allocation is efficient in the case in which there are no wedges.

We can generalize the welfare decomposition from the previous section for different groups of labor under the assumptions where the utility and production function is homogeneous of degree one. In particular, we can rewrite the change in $\bar{U}$ as:

$$d\ln\bar{U}=\underbrace{-\sum_{n,i,s,g}\alpha_{ng}\beta_{isg}\left(\tilde{\lambda}_{ng}\lambda_{nsg|n}\lambda_{nisg|ns}\right)\cdot d\ln d_{ni}}_{\text{“Pure” effect commuting costs}} \tag{E.16a}$$

$$\underbrace{-\sum_{n,i,s,g}\pi_{ns}\pi_{nis|s}\left(\alpha_{ng}\beta_{isg}\tilde{\lambda}_{ng}\right)d\ln\tau_{ni}}_{\text{“Pure” effect trade costs}} \tag{E.16b}$$

$$+\underbrace{\left(\sum_{n,i,s,g}\alpha_{ng}\beta_{isg}\tilde{\lambda}_{ng}\lambda_{nsg|n}\lambda_{nisg|ns}\left(\frac{t_{isg}-\bar{t}}{1+\bar{t}}\right)d\ln\tilde{L}_{nisg}\right)}_{\text{Allocative efficiency}} \tag{E.16c}$$

$$+\underbrace{\sum_{n,i,s,g}\frac{\beta_g}{\sigma_s-1}\left(\frac{1+t_{isg}}{1+\bar{t}}\right)d\tilde{\lambda}_{isg}}_{\text{Agglomeration Forces}}. \tag{E.16d}$$

This result is similar to the one obtained by Baqaee and Farhi (2020) in GE models. However, this expression is in the context of an urban model in which firms face iceberg trade costs and workers face i) commuting costs, and ii) are indifferent to live across locations within the city.

E.3 Equilibrium Conditions - Exact Hat Algebra

In this section, I solve for the equilibrium conditions and change in total welfare using exact hat algebra as in Dekle et al. (2008). I define the percentage change of a variable as:

$$\hat{x}=\frac{x'}{x}$$

then, the change in the average utility is

$$\hat{\bar{U}} = \left(\sum_n \lambda_n \hat{P}_n^{-\alpha\eta} \hat{r}_n^{-(1-\alpha)\eta} \hat{W}_n^{\eta} \right)^{\frac{1}{\eta}}, \tag{E.17}$$

where $\lambda_n \equiv \frac{W_n^{\eta} P_n^{-\alpha\eta} r_n^{-(1-\alpha)\eta}}{\sum_{n'} P_{n'}^{-\eta} W_{n'}^{\eta}}$ is the share of residents in location n in the pre-period. The change in the price and wage indices is given by the following expressions:

$$\hat{P}_{ns} = \left(\sum_i \pi_{ni|s} \hat{p}_{is}^{1-\sigma_s} \right)^{\frac{1}{1-\sigma_s}} \tag{E.18a}$$

$$\hat{P}_n = \left(\sum_i \pi_{ns} \cdot \hat{P}_{ns}^{1-\xi} \right)^{\frac{1}{1-\xi}} \tag{E.18b}$$

$$\hat{W}_{ns} = \left(\sum_i \lambda_{nis|ns} \cdot \hat{w}_{is}^{\theta_s} \hat{d}_{ni}^{-\theta_s} \right)^{\frac{1}{\theta_s}} \tag{E.18c}$$

$$\hat{W}_n = \left(\sum_s \lambda_{ns|n} \cdot \hat{W}_{ns}^{\kappa} \right)^{\frac{1}{\kappa}}. \tag{E.18d}$$

The change in the residence, sector, and workplace choice probability is:

$$\hat{\lambda}_n = \frac{\hat{P}_n^{-\eta} \hat{W}_n^{\eta}}{\sum_{n'} \lambda_{n'} \cdot \hat{P}_{n'}^{-\eta} \hat{W}_{n'}^{\eta}} = \frac{\hat{P}_n^{-\eta} \hat{W}_n^{\eta}}{\hat{\bar{U}}^{\eta}} \tag{E.19a}$$

$$\hat{\lambda}_{ns|n} = \frac{\hat{W}_{ns}^{\kappa}}{\sum_k \lambda_{nk|n} \cdot \hat{W}_{nk}^{\kappa}} = \frac{\hat{W}_{ns}^{\kappa}}{\hat{W}_n} \tag{E.19b}$$

$$\hat{\lambda}_{nis|ns} = \frac{\hat{w}_{is}^{\theta_s} \hat{d}_{ni}^{-\theta_s}}{\sum_l \lambda_{nls|ns} \cdot \hat{w}_l^{\theta_s} \hat{d}_{nl}^{\theta_s}} = \frac{\hat{w}_{is}^{\theta_s} \hat{d}_{ni}^{-\theta_s}}{\hat{W}_{ns}^{\theta_s}}. \tag{E.19c}$$

And the change in the expenditure shares is:

$$\hat{\pi}_{ns} = \frac{\hat{P}_{ns}^{1-\xi}}{\sum_k \pi_{nk} \hat{P}_{nk}^{1-\xi}} = \frac{\hat{P}_{ns}^{1-\xi}}{\hat{P}_n^{1-\xi}} \tag{E.20a}$$

$$\hat{\pi}_{ni|s} = \frac{\hat{p}_{nis}^{1-\sigma_s}}{\sum_l \pi_{nls|s} \hat{p}_{nls}^{1-\sigma_s}} = \frac{\hat{p}_{nis}^{1-\sigma_s}}{\hat{P}_{ns}^{1-\sigma_s}}. \tag{E.20b}$$

The change in the average labor income and aggregate expenditure is:

$$\hat{\bar{y}}_n = \sum_{i,s} \lambda_{nis}^{Y} \hat{\lambda}_{nis|ns} \hat{\lambda}_{ns|n} \hat{w_{is}}, \tag{E.21}$$

where $\lambda_{nis}^{Y} \equiv \frac{\lambda_{nis|ns} \lambda_{ns|n} w_{is}}{\bar{y}_n}$. Then, the change in X_n is:

$$\hat{X}_n = (1 \hat{+} \bar{t}) \left(\omega_{nL} \hat{\bar{y}}_n \hat{\lambda}_n + \omega_{nZ} \hat{q}_n + \omega_{nH} \hat{r}_n \right), \tag{E.22}$$

where $\omega_{nL} \equiv \frac{\bar{y}_n L_n}{\bar{y}_n L_n + q_n Z_n + r_n H_n}$, $\omega_{nZ} \equiv \frac{q_n Z_n}{\bar{y}_n L_n + q_n Z_n + r_n H_n}$, and $\omega_{nH} \equiv \frac{r_n H_n}{\bar{y}_n L_n + q_n Z_n + r_n H_n}$. Then, the goods market clearing condition using exact hat algebra for each location i and sector s is:

$$\hat{w}_{is} \sum_n \tilde{\lambda}_{ni} \hat{\lambda}_{nis|ns} \hat{\lambda}_{ns|n} \hat{\lambda}_n = \sum_n \pi^X_{nis} \hat{\pi}_{ns} \hat{\pi}_{nis|s} \hat{X}_n, \tag{E.23}$$

where $\tilde{\lambda}_{ni} = \frac{\lambda_{nis}}{\sum_{n'} \lambda_{n'is}}$, and $\pi^X_{nis} = \frac{\pi_{ns} \pi_{nis|s} X_n}{\sum_{n'} \pi_{n's} \pi_{n'is|s} X_{n'}}$. I compute the counterfactuals solving the previous system of equations E.23.

E.4 Model with ex-ante firm decision

In this section, I present a version of the model in which firms decide whether to operate in the formal or in the informal sector. The model is based on Ulyssea (2018) and Dix Carneiro et al. (2018) in which firms that operate in the informal sector face a distortion that increases with size. There is a infinite mass of potential entrants that exit at an exogenous rate δ_s. The labor supply function takes the same form as in the main text. On the other hand, firms make two decisions. First, they decide whether to enter in the labor market and conditional on entry whether to operate in the formal or informal sector based on a pre-entry signal and a entry fixed cost. Second, firms decide the location in the city in which they are going to operate based on an extreme value type II shock. There is no production fixed cost.

The total operational profits of firm ω that operate in location i and sector s, and sells to n is given by:

$$\pi^{op}_{nis}(\omega) = \frac{1}{\sigma_s - 1} \left(\frac{\tau_{ni} (w_{is}[1 + t_{isL}])^{\beta} (q_i[1 + t_{isZ}])^{1-\beta}}{z(\omega) \epsilon_{is}(\omega)} \right)^{1-\sigma_s} P_n^{\sigma_s - 1} \tilde{X}_{ns},$$

$$\pi^{op}_{is}(\omega) = (1 - \upsilon_{is}(r_{is}(\omega))) \sum_n \pi^{op}_{nis}(\omega),$$

where $z(\omega)$ is the pre-entry signal, $\epsilon_{is}(\omega)$ is an idiosyncratic productivity shock of firm ω that varies across locations, and $\upsilon_{is}(r_{is}(\omega))$ is a distortion that captures the probability of getting caught if firm ω operates in the informal sector. This probability increases with the size and revenue $r(\omega)$ of firm ω. I assume that the idiosyncratic shocks are drawn from a Frechét distribution with shape parameter ψ and scale parameters A_{is}. Then, the share of firms with pre-entry signal z from sector s that operate in location i is:

$$\mu_{is}(z) = \frac{A_{is} \pi_i^{\psi} s(\omega)}{\sum_l A_{ls} \pi_l^{\psi} s(\omega)}. \tag{E.24}$$

With these assumptions, the expected value of entry for a firm with pre-entry signal z that operates in sector s is:

$$V^e_s(z, \vec{w}_{is}) = \frac{z^{\sigma_s - 1}}{\delta_s} \left(\sum_i \left[(1 - \upsilon_{is}(r_{is})) A_{is} \sum_n \left(\frac{\tau_{ni} (w_{is}[1 + t_{isL}])^{\beta} (q_i[1 + t_{isZ}])^{1-\beta}}{z(\omega)} \right)^{1-\sigma_s} P_n^{\sigma_s - 1} \tilde{X}_{ns} \right]^{\psi} \right)^{\frac{1}{\psi}}. \tag{E.25}$$

A firm decides to enter and operate in sector k if the following condition holds:

$$V_k^e(z, \vec{w}) - E_k \geq \max\{V_{-k}^e(z, \vec{w}) - E_{-k}, 0\}. \tag{E.26}$$

Because the average expected profits increase with size, and the distortion also increases with size, there are two cutoffs of the pre-signal productivity z that determine the entry to market and whether a firm operates in the informal or the formal sector. Let's define the entry cutoff as z_{E}, and the informality cutoff as z_{I}. Then, the labor demand in location i and the informal and formal sector are given by:

$$L_{i\mathrm{I}} = \frac{\beta w_{i\mathrm{I}}^{-1}}{F(z_{\mathrm{I}}) - F(z_{\mathrm{E}})} \int_{z_{\mathrm{E}}}^{z_{\mathrm{I}}} \mu_{i\mathrm{I}}(z) r_{i\mathrm{I}(z)} dF(z) \tag{E.27}$$

$$L_{iF} = \frac{\beta w_{iF}^{-1}}{1 - F(z_{\mathrm{I}})} \int_{z_{\mathrm{I}}}^{\infty} \mu_{iF}(z) r_{iF(z)} dF(z), \tag{E.28}$$

where the variable $r_{is}(z)$ represent the average revenue of a firm with presignal z. The labor supply function takes the same form as in the main text, and the equilibrium is determined by equalizing the labor demand and labor supply. Similarly, to solve for the commercial floor space equilibrium, the demand function is given by:

$$\tilde{Z}_i^D = q_i^{-1}(1-\beta)\left(\frac{1}{F(z_{\mathrm{I}}) - F(z_{\mathrm{E}})} \int_{z_{\mathrm{E}}}^{z_{\mathrm{I}}} \mu_{i\mathrm{I}}(z) r_{i\mathrm{I}(z)} dF(z) + \frac{1}{1 - F(z_{\mathrm{I}})} \int_{z_{\mathrm{I}}}^{\infty} \mu_{iF}(z) r_{iF(z)} dF(z)\right). \tag{E.29}$$

On the other hand, the equilibrium equations for the residential floor space are the same as in the main text. Following the logic from Ulyssea (2018) and Dix Carneiro et al. (2018) this equilibrium exists.