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

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Abstract

Can transit infrastructure improve allocative efficiency by reducing informality? This paper proposes a new mechanism to account for the significant gaps in marginal products of labor across plants in developing countries: the high commuting costs to transit within cities that prevent workers from accessing formal employment. To test this mechanism, I combine a rich collection of administrative microdata and exploit the construction of new subway lines in Mexico City. First, I provide evidence that firms with higher wedges (formal) concentrate in the city center, while informal firms in the outskirts. Second, I show that informal workers are more sensitive to commuting costs than their formal counterparts, and as a consequence, work closer to their residence. Third, estimating a series of difference-in-differences specifications, I find that transit improvements reduce informality rates by four percentage points in nearby areas to the new stations. I develop a spatial general equilibrium model considering both the direct effects under perfectly efficient economies and the allocative efficiency margin due to wedges across sectors and locations. I quantify and decompose the welfare gains of the new infrastructure after estimating the key elasticities of the model. Changes in allocative efficiency driven by workers' reallocation to the formal sector explain approximately 17-25% of the total gains, and average real income per every dollar spent on the infrastructure increases by 20% relative to a perfectly efficient economy.

Keywords: Informality, allocative efficiency, urban transit infrastructure.

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1 Introduction

Poor transportation infrastructure is a common characteristic of cities in developing countries. For instance, in Mexico City, it takes a typical low-skilled worker approximately two to three hours to commute to jobs in the center of the city. In recent decades, governments around the world have spent billions of dollars on infrastructure projects to facilitate commuting. 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.[1] In this paper, I study the economic impacts of transit infrastructure in Mexico City, considering both the direct effects in perfectly efficient economies and the role played by distortions in allocative efficiency.

Labor market informality is one of the most significant sources of distortions in low and middle-income countries, with important implications for aggregate efficiency. Within developing countries, 50 to 60 percent of total employment is informal. Informal establishments are less productive than formal firms, avoid paying taxes, and do not make social security contributions to their workers.[2] As a consequence, the informal sector creates labor wedges that cause factor misallocation, which ultimately lowers aggregate total factor productivity (TFP) (Banerjee and Duflo, 2005; Hsieh and Klenow, 2009; Restuccia and Rogerson, 2008). These inter-sectoral distortions between the formal and informal sector imply that any policy or shock that impacts informality may have first-order effects on aggregate welfare through an allocation margin.[3]

This study explores the link between transit improvements, informality, and aggregate efficiency at the city level. I test whether infrastructure projects that facilitate transit within a city improve allocative efficiency by reallocating workers from the informal to the formal sector. As a result, aggregate gains from these projects can be larger relative to standard urban models that assume perfectly efficient economies. The core intuition is that in cities in developing countries, workers in remote locations prefer to work in low-paid informal jobs near their residence rather than incurring the high commuting costs to access formal employment. Transit developments may provide better access to formal jobs, leading to an expansion of the formal sector and improving 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 effect of urban transport improvements on worker reallocation across the formal and informal economy. Second, I rationalize these results through the lens of a quantitative spatial equilibrium model of the city. To this end, I extend recent theoretical work (Ahlfeldt et al., 2015; Allen et al., 2015; Tsivanidis, 2019) by adding inter-sectoral distortions and factor misallocation to an urban quantitative framework. I provide a formula that decomposes the welfare gains from transit developments into a "direct" effect and an allocative efficiency term following Baqaee and Farhi (2019). This latter term captures two different components: factor misallocation and

[1] See e.g., Atkin and Khandelwal (2019) for a recent review of market distortions in the context of the gains from market integration, and Busso et al. (2012); Levy (2018) for the effect of distortions on total factor productivity in the Mexican context.

[2] See Gollin (2002, 2008) and La Porta and Shleifer (2008, 2014) for the relationship between the prevalence of the informal sector and economic development.

[3] For example, see McCaig and Pavcnik (2018) and Dix Carneiro et al. (2018) for the case of trade policies and their effect on the informal economy and the aggregate gains from trade. The former paper studies the effect of the Free Trade Agreement between the US and Vietnam, and the latter the impact of the Brazilian trade liberalization episode.

agglomeration externalities that differ between the two sectors.[4]

Mexico City constitutes a relevant and informative case study for several reasons. First, it has a dense concentration of economic activity, accounting for around 8.9 million people and involving the transport of millions of workers every day. Second, the Mexican case is typical for developing countries, especially in Latin America, where more than 50% of the urban labor force and 70% of economic establishments are informal.[5] Furthermore, the city constructed a new primary subway line in the early 2000s, connecting remote areas in the north with the center of the city. This line was planned several years earlier, suggesting that the opening dates were uncorrelated with local demand and supply shocks. Moreover, Mexico City collects unique data that I use to estimate the impact of transit improvements considering the effect on informality. Throughout, I use the standard definition of informality: a worker is informal if they do not receive social security benefits based on the contractual relationship between the worker and her employer.

At the center of the analysis is a rich collection of administrative microdata that allows me to observe the geography of jobs and worker residences for both the formal and informal sectors at the high granular census-tract level. In the analysis, I use four main sources of data. First, I use confidential microdata from several rounds of the Mexican Economic Census, covering the universe of business establishments located in Mexico City. Second, I use the microdata of the Mexican Population Census to determine the residence of both formal and informal workers. Third, I use detailed information on the transportation network in Mexico City, including how it evolved across different modes of transportation, which I complement with transportation diaries (origin-destination survey data). Additionally, I use the intercensal 2015 survey that allows me to construct commuting and trade flows at the municipality level for both sectors. I also use standard household survey data to calibrate some of the moments of the model.

In the first part of the paper, I document three empirical facts that suggest a negative relationship between the accessibility of jobs and informality.

First, I exploit cross-sectional variation among informal vs. formal workers to show that informal workers spend less time commuting, make fewer trips, and work closer to home relative to their formal counterparts. For instance, informal workers spend 40% less time commuting on average, and are 10 percentage points more likely to work in the same municipality in which they reside. This implies that informal workers are more sensitive to commuting costs than formal workers, indicating that the commuting elasticity in the informal sector is higher. These findings are robust to controlling for different sets of fixed effects (e.g., if the specification compares formal and informal workers that use the same transportation-mode and live in the same municipality).

Second, I compare the location of informal and formal workers. I document that formal jobs concentrate in the west and center of the city, where most economic activity takes place. By contrast, most informal workers reside in the east and on the periphery of the city. This fact suggests that high commuting costs induce workers in the outskirts to prefer working in an informal business rather than working in a formal job in central locations.

[4]See Bartelme et al. (2019) for recent work that studies the effect of optimal policies when agglomeration externalities differ across sectors or locations.

[5]See Perry et al. (2007) and Ulyssea (2018) that document informality rates in Latin America. In the region, the informal economy varies from 35% in Chile to 80% in Perú.

Third, I exploit the construction of a new subway line that connected remote locations with the center of Mexico City as a transit shock to provide causal evidence that transit infrastructure leads to a decrease of informality rates. Specifically, I estimate a series of difference-in-differences specifications that use variation in access to new transit as identifying variation. These specifications control for initial characteristics of census tracts and capture changes in informality trends 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, including several unexpected and multi-year delays in the opening schedule. I further corroborate this assumption by documenting no apparent pre-trends among the most affected locations in the preceding periods. The main finding is that informality rates decrease in locations close to the new stations. Workers' informality rates decrease by 2 to 4 percentage points after the construction of the new line, and firms' informality rates decrease by 1 to 3 percentage points. These estimates represent a 6.7% decrease in workers' informality rates, using the average informality rate in the baseline year as a benchmark. Similarly, I find that the ratio of formal to informal residents increases by approximately 7% after the shock in locations nearby to the new stations.

As a robustness check of the difference-in-difference specification, I compare the new line with similar planned metro lines that were not completed over this period for unrelated reasons using an expansion plan from 1980. Reassuringly, this robustness check yields similar estimates to the baseline specification. Another potential concern to identification is a change in the composition of households in areas nearby to the new stations. To show that this is not the case, I also estimate the difference-in-difference specification using household characteristics as dependent variables. I find that the transit shock did not lead to changes in the composition of households based on observable characteristics.[6]

To calculate and decompose the welfare gains from transit improvements, I build a quantitative model with multiple sectors and wedges that captures the three facts from the empirical analysis. The model allows me to quantify the aggregate effects of new infrastructure, considering the additional impact on factor allocation. Following Baqaee and Farhi (2019), I provide a formula that decomposes the welfare effects of any trade/commuting costs shock into two different components: a "direct" effect term and an allocation term. The new margin depends on two components: factor misallocation and agglomeration externalities that differ between the two sectors. In the standard framework, in which the economy is efficient, I show that the main result from Hulten (1978) holds. The welfare gains from transit developments can be measured through the classic cost-time-saving approach (Hulten, 1978; Train and McFadden, 1978).[7] However, when the economy is inefficient, the sufficient statistic is expanded with two additional terms that account for the allocation mechanism. Intuitively, the sign of this additional impact will depend on whether the shock reallocates workers to sector-locations with larger wedges or to sectors with bigger agglomeration forces.[8] The logic is similar to that in Hsieh and

[6]Moreover, the quantitative model accounts for employment and location decisions within the city. Thus, I consider the change in household characteristics after the transit shock based on unobservables.

[7]The objective of this formula is provide the main intuition of the allocation channel. Since this is a 1st-order approximation, the assumption for this formula to capture actual changes in welfare is that the reduction in commuting costs is infinitesimal. For this reason, I compute the counterfactuals using percentage changes.

[8]The third term arises in the presence of agglomeration externalities and trade imbalances as in Fajgelbaum and Gaubert (2019). In the case of the efficient economy, I am assuming trade balances. In the inefficient economy, the labor wedges create

Klenow (2009) and Baqaee and Farhi (2019): sector-locations with larger wedges are too small as a share of the economy since this equilibrium is not a first-best allocation. Then, if a shock reallocates workers to firms bearing higher distortions, the aggregate welfare gains are larger.

I calibrate the model using structural relationships. The key parameter to estimate is the labor supply elasticity across sectors, which governs the reallocation of workers from the informal to the formal sector. I follow Tsivanidis (2019) and calculate measures of market access for residents and firms by sector. I recover this key elasticity by running a triple difference estimator that associates changes in factor allocation between the formal and informal economy with changes in market access, exploiting variation across locations after the transit shock. The estimates for the parameter that I find, around 1.5, are lower than those found in the previous literature, but they are consistent with the theoretical assumptions of the model. Intuitively, if a transit shock connects workers to better formal jobs relative to informal jobs, workers reallocate from the informal to the formal sector, generating additional welfare gains through a margin of allocative efficiency.

I also estimate other key parameters of the model, such as the trade and commuting elasticities for both sectors. For this exercise, I use additional microdata from the 2015 Intercensal survey and the 2017 Origin-Destination survey. I use trips to work and shops to build commuting flows and trade flows across municipalities and different transportation modes in Mexico City. I estimate commuting elasticities and trade elasticities by running gravity equations relating trade/commuting flows to the average time spent to move across locations in the city. Intuitively and consistent with the reduced-form evidence, I find that the commuting elasticity for the informal sector is larger. This implies that informal workers are more sensitive to commuting costs than their formal counterparts and that informal jobs are easier to substitute for workers. Moreover, I also find that the trade elasticity in the informal sector is higher than in the formal sector, suggesting that agglomeration forces are larger for formal firms.

Next, I quantify and decompose the welfare gains from the transit shock by varying trade/commuting costs in the GE model. I find that the allocation margin drives a significant fraction of the total gains. I am able to construct commuting and trade flows from an initial equilibrium using the market access measures described above and recovering scale parameters of the model. I compute the counterfactual using the estimates of the key elasticities, the initial equilibrium conditions, and exact hat algebra as in Dekle et al. (2008) (DEK). The results suggest that the new subway line increased welfare by 1.58%. I find that the direct effects explain approximately 83% of the total gains, while the reallocation of workers from informal to formal firms explain 14% and the remaining 3% of gains are driven by the agglomeration externality component when the strength of the forces differs across sectors.[9] The counterfactual analysis also suggests that the reductions in commuting and trade costs account for a similar amount of the total gains.

In terms of the cost-benefit analysis, the allocative efficiency margin increases net welfare by a considerable proportion. According to official documents from the Government of Mexico City, the net present value of the total cost of a subway line with 20 km and 20 stations is approximately 0.72% of

trade imbalances, and the third term shows up.

[9] I compute two counterfactuals. The first one allows workers to migrate within the city. The second one holds constant the population in each census tract. In the case in which workers do not migrate, the welfare gains are only 1.27%. The direct effects explain 75% of the gains, the resource misallocation margin 17%, and the differences in agglomeration externalities between the two sectors the remaining 8%.

the total GDP of Mexico City. Since line B increases welfare between 1.30% and 1.58%, this represents a net gain of around $2.00 USD per every dollar spent on the infrastructure. This gain would have been lower without considering the allocative efficiency margin in a perfectly efficient economy. For example, in the case of migration, the reallocation of workers from the informal to the formal sector increases the average real income net of the total cost of the project by 20% relative to a perfectly efficient economy.

I run other counterfactuals in which I simulate other types of policies that the government can implement to reduce informality rates. The results suggest that transit infrastructure can be an effective policy tool to reduce informality by connecting informal workers with formal jobs. For example, to reduce informality rates by 2% at the aggregate level, which is the result of the market access approach, the government needs to reduce the entry formal fixed cost by more than 25% or increase the entry informal fixed cost by more than 40%.

The findings of this project suggest that in terms of future research is important to consider the allocative efficiency margin in the optimal allocation of infrastructure. Recent papers such as Fajgelbaum and Schaal (2017), Balboni (2019), and Santamaría (2020) have estimated the infrastructure misallocation in spatial general equilibrium models. My results suggest that when a social-planner decides where to allocate infrastructure, there are also first-order effects driven by the resource misallocation component, which are important to take into account. My findings imply that connecting remote locations with high-efficient locations can increase aggregate welfare more than connecting similar places where the composition of workers is similar.

This paper speaks 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 role of allocative efficiency on TFP and the main causes of the informal economy. This latter strand is related to a large literature in international economics that has estimated the impact of trade reforms on allocative efficiency in the presence of domestic distortions.

First, a new strand of literature [including (Ahlfeldt et al., 2015; Baum-Snow, 2007; Gonzalez-Navarro and Turner, 2018; Heblich et al., 2018; Monte et al., 2018; Tsivanidis, 2019)] has explored the impact of transit infrastructure that facilitates commuting. For example, Tsivanidis (2019) assesses the welfare and distributional effects of a new Bus Rapid Transit (BRT) system in Bogotá, and Heblich et al. (2018) study the economic consequences of the subway in London. My paper adds to this literature by examining the effect of transit infrastructure on allocative efficiency. I depart from standard urban economic models by adding distortions and resource misallocation, and by showing with a first-order approximation that the presence of the informal sector creates additional first-order effects. My main hypothesis is that, by separating residence and workplace, transit improvements have an additional effect on allocative efficiency.[10]

This paper also relates to a literature that has emphasized the role of factor misallocation in lowering aggregate TFP (Banerjee and Duflo, 2005; Hsieh and Klenow, 2009; Restuccia and Rogerson, 2008).

[10] Another paper that studies a distortion in the context of an urban model is Pérez Pérez (2018). He focuses on a different question, assessing the role played by the minimum wage on aggregate employment and commuting patterns across US cities.

These studies have shown that the dispersion in distortions across firms and sectors generates factor misallocation, and that this is higher in developing countries than in more advanced economies. In the particular case of Mexico, Busso et al. (2012) show that if workers reallocate from the informal to the formal sector by eliminating wedges, TFP increases by approximately 50%. Different studies have aimed to understand the main causes of the large levels of resource misallocation in developing countries. Some of the primary explanations consist of regulations, markups, and the wedges caused by the informal sector. One of my contributions is that following Baqaee and Farhi (2019), I decompose the total welfare into a "direct" effect and an allocation term that considers the reallocation of workers across the formal and informal economy.

Third, my work also relates to a strand of the international economics literature that has studied the gains from trade, taking into consideration the allocative efficiency channel. This literature was recently reviewed by Atkin and Khandelwal (2019), who discuss the role of distortions on the aggregate gains from trade. 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., 2016; Edmond et al., 2015; Holmes et al., 2014; Hornbeck and Rotemberg, 2019). Similar to my paper, some studies have analyzed the role of inter-sectoral distortions (Święcki, 2017), and the effect of trade on informality (Dix Carneiro et al., 2018; McCaig and Pavcnik, 2018; McMillan and McCaig, 2019). For example, McCaig and Pavcnik (2018) assess the impact of the free trade agreement between the US and Vietnam on informality and aggregate productivity. While this literature focuses on trade reforms that affect labor demand, my paper examines the impact of commuting and trade market access measures. For this reason, I can study the effect of a shock affecting both labor demand and supply.

Finally, other studies, such as Moreno-Monroy and Posada (2018) and Suárez et al. (2016) have also explored the relationship between commuting and informality. They argue that the high commuting costs to a formal job faced by a large part of the population increase informality rates in developing countries. My paper contributes to this literature by providing causal evidence on the relationship between transit infrastructure and informality for both workers and residents exploiting the transit shock in Mexico City. My work also contributes, by measuring the economic impact of these projects on the allocative efficiency margin through the lens of a quantitative model.

The rest of the paper is structured as follows. Section 2 introduces the setting of my study in Mexico City and describes the transit shock. Section 3 presents the three empirical facts and the reduced-form evidence of the effect of commuting on informality. Section 4 develops an urban quantitative model with multiple sectors and inter-sectoral distortions. Section 5 estimates the main parameters of the model. Section 6 quantifies and decomposes the welfare gains from transit improvements. 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 decreed the creation of a decentralized public office to build, operate, and run a rapid transit of subterranean courses for the public transport of 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 was an instrument that determined the mobility goals that the transport system needed to satisfy over the long run. These goals delineated how the subway should be extended, based on best practices in urban development and operational constraints for the project. The *Plan Maestro 1985-2010* underwent some modifications from what the Government initially had planned. These modifications responded mainly to changing patterns of demand for transportation in Mexico City, which forced the Government to redesign some lines. I use this as part of my empirical strategy, by comparing the unplanned modifications to the subway lines with the original and unexecuted 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 CBD of Mexico City. It was inaugurated in 2000 and was initially planned as part of *Plan Maestro 1985*, which reduces potential endogeneity concerns between the opening of the new stations and local demand/supply shocks. The line has approximately 20kms long and includes 21 stations. It connected the metropolitan area of the city 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.[11] As a result, line B has the distinct feature of connecting informal workers with formal employment. To date, it is the fourth line with the 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 approximately $2,900 million in 2014 USD dollars, which represents 0.7% of the total GDP of Mexico City.

Figure 4 plots a map of the Mexico City subway system in 2000, highlighting the lines that I use in my empirical strategy. Line B is the purple line that connects the north-eastern area, including locations in Mexico State, with the center of the city. I also use Line 12 and Line C as robustness checks; Line C - the green line- was planned as a feeder line in the early 2000s, similar to line B. However, the city Government never constructed it. Line 12 -the red line- is the newest subway line in Mexico City and was opened in 2012.

2.2 Informality

I use two definitions of informality as in Busso et al. (2012); Kanbur (2009), and Levy (2018). 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.[12] These workers can be salaried and non-salaried workers. The second definition is a more restrictive one, as it only considers non-salaried workers of the first group,[13] for example, family members that work in a household business or are

[11] In the appendix, I relate census tract characteristics before the shock to line B to show this result.

[12] Social security benefits include health care, savings for retirement, social benefits for recreation, and invalidity allowances.

[13] The second group is a subset of the first group.

self-employed.

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 1 compares informality rates (following the standard definition) between countries in Latin America and the Caribbean and the average of the OECD. Informality rates in the entire region are very high. The mean across the region is 50%, which is a much higher value 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 even bigger when we compare Mexico to other countries with a similar income level, such as Argentina or Colombia.[14]

The presence of the informal sector and the fact that informal firms avoid paying taxes create a labor wedge between informal and formal firms. According to recent estimates, a firm that fully complies with salary regulations is expected to pay 18% of wages as social security (Busso et al. (2012); Levy (2018)).These wedges create distortions across firms that ultimately decrease welfare and TFP. Figure 2 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. However, due to the presence of labor wedges -social security taxes-, conditional on productivity, informal firms are too large, while formal firms are too small relative to a social optimum.[15] As a consequence, reallocating workers from the informal to the formal sector may lead to productivity gains that impact welfare. Different studies have examined the gains from removing the informal sector in Mexico, finding that TFP would increase by approximately 50% (Busso et al., 2012). My project aims to understand one potential channel to solve this problem: namely, connecting formal employment with the informal labor force.

In the next section, I show how informality rates are unequally distributed across the city. On the one hand, most formal firms are usually located in the center. On the other, informal workers usually live in the periphery. This paper aims to understand whether urban transportation can reduce informality rates and increase productivity by connecting the informal labor force with formal employment.

3 Data and motivating facts

In this section, I describe the data and provide evidence of three empirical facts relevant to thinking about the relationship between commuting and informality.

3.1 Data

My primary unit of observation is the urban census tract (Ageb in the Mexican micro-data). I use a sample of approximately 3,500 census tracts from 116 different neighborhoods and 24 different municipalities, 16 municipalities of which are in Mexico City and 8 of which are adjacent municipalities from the State of Mexico. 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.

[14] I do not observe the second definition of informality in other countries.

[15] Busso et al. (2012) and Levy (2018) study the formal vs. informal sector in the Mexican context, and show that wedges are higher for formal than informal firms.

The first source of information is standard GIS data to identify the location of the transportation network and the new transit subway lines. I also use data of roads and highways in Mexico City to calculate commuting times for different transportation modes using the network analysis toolkit from ArcGIS. With this exercise, I can estimate commuting/trade costs before and after the transit shock.

The second source of data are the Mexican Economic Censuses collected by INEGI. This is an establishment-level data set that provides standard information such as sales, value added, number of workers, salaried workers, social security, and other outcomes. This census is carried out every five years starting in 1994. I am able to define the informal sector at the establishment level using social security payments following the definitions from section 2 (Busso et al., 2012; Levy, 2018). I categorize firms and workers in four different groups based on labor market regulations. I also calibrate wedges for each location and sector using wage bill, sales, and social security payments.

The third source of information is the Mexican Population Census. This census is carried out every ten years, and INEGI provided me with the data since 2000. With this information, I am able to calculate the number of informal, formal, and total residents in each location. For some years, the Populations Censuses also report other variables such as household income or job characteristics the week before the interview. With this data, I observe the number of informal and formal residents in each location from social security information. Moreover, I use the Intercensal 2015 survey that provides information on the workplace, residence, and transportation mode for formal and informal workers at the municipality/locality level. This data allows me to observe commuting flows in Mexico City for each sector.

I also use the 2017 origin-destination survey collected in the commuting zone area of Mexico City. I use this data for two purposes. First, I infer trade flows across the city using trips to restaurants, and other types of shops at different hours of the day. Second, I show some motivational facts considering commuting patterns, for example, that informal and low-skilled workers commute less and make fewer trips than their formal counterparts.

Finally, I am complementing my results with standard household survey data from the ENOE. I calibrate some of the parameters from the model using this data.

3.2 Empirical Facts

I now describe three empirical facts that show a negative relationship between informality rates and the accessibility of formal jobs in Mexico City: 1) Informal workers are more sensitive to commuting costs and spend less time commuting; 2) informal workers are located in areas in which they have poor access to formal employment; and 3) informality rates decrease with transit improvements that connect informal workers to formal employment. For the first fact, I compare the average commuting time and workplace decisions between workers in the informal vs. the formal sector. For the second fact, I compare the location of formal/informal jobs and the residence of informal/formal workers. Finally, the third fact exploits variation over time and across location after the construction of a new subway line that connected northeastern locations in the state of Mexico with the center of Mexico City. It shows that locations close to the new subway line experienced a decrease in informality rates. The identification assumption is that the opening of the new stations is uncorrelated with local demand/supply shocks that affect informality rates. This seems plausible since line B was planned several years before. I also show that in terms of observed covariates, the change in the composition of household is negligible.[16]

3.2.1 Cross-sectional variation

Fact 1: *Informal workers commute less time and work closer to their home relative to formal workers.*

For the first fact, I use the intercensal 2015 survey and exploit cross-sectional variation comparing the average commuting time, and workplace decisions of informal vs. formal workers. With this data, I am able to observe the residence and workplace for each individual at the municipality level. Moreover, it also reports the average commuting time for each worker. I use the standard definition of informality based on the contractual relationship of the worker and whether the worker has access to social security. I also restrict the sample to individuals who worked the week before the interview. I run the following linear probability model to test whether informal workers spend less time commuting and work closer to their residence:

$$y_i = \beta_0 + \beta_1 \text{Informal}_i + \gamma X_i + \gamma_{l(i)} + \gamma_{n(i)} + \gamma_{m(i)} + \epsilon_i, \tag{3.1}$$

where y_i is a dummy variable that takes the value of 1 if individual i commutes to a different municipality than the one he/she resides, whether he/she works in the CBD of Mexico City, or whether their average commuting time is within some window (i.e., 16 to 30 minutes); X_i is a vector of individual characteristics that includes: age groups, educational groups, a gender fixed effect, relationship with the household head fixed effects, and a dummy variable indicating whether the individual has an African or 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; and, ϵ_i is the error term of the regression.

Table 1 reports the results for the dummy variables of whether the worker commutes to another municipality; or whether he/she works in the CBD. The results imply that informal workers spend less time commuting than formal workers. For instance, the probability of commuting to a different municipality decreases on average, between 8.0 to 25.0 percentage points for workers in the informal sector. Similarly, informal workers are less likely to work in the CBD of Mexico City relative to formal workers between 4.0 to 9.0 percentage points. In the fourth column, I show that differences in transportation modes are not driving these effects by including transportation mode fixed effects. This specification compares informal vs. formal workers that usually use the same mode of transportation, and even though that the point estimate decreases, the main result holds.

To provide more evidence of this channel, figure 5 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 a dummy variable that takes a value of 1 if the worker is informal. From the figure, it is clear that informal workers spend less time on commuting than their formal counterparts. For instance, the first bar shows that informal workers are more likely to work from their

[16]The model will account for compositional changes in terms of unobserved idiosyncratic shocks by considering migration decisions within the city.

home in 13 p.p. relative to formal workers. Similarly, they are more likely to spend less than 15 minutes in commuting time, suggesting that on average, informal workers work closer to their home. On the other hand, formal workers are more likely to spend more than 30, 60, or 120 minutes commuting than informal workers. For example, formal workers are more likely in approximately 10 p.p. to spend more than 60 minutes commuting each day to get to their workplace than informal workers.

Overall, the results from table 1 and figure 5 suggest that informal workers spend less time commuting than their formal counterparts and work closer to their home. The main point from this finding is that informal workers are more sensitive to commuting costs than their formal counterparts.

Fact 2: *Most formal jobs are located in the central areas of the city, while most informal workers reside in the outskirts.*

The second fact shows that most formal jobs are available in the center and west of the city, while informal workers reside in less connected areas. As a consequence, workers that can not bear the high rents from central locations of the city, and live in areas with poor access to formal jobs prefer to work in an informal business close to their residence.

Figure 3 plots a heat map of deciles of workers' and residents' informality rates in Mexico City and adjacent municipalities of the state of Mexico. As shown in figure A2 of the appendix, locations with the largest level of economic activity are in the middle-west of Mexico City.[17] From the figure, it is clear that in the middle-west and center of the city, informality rates are lower than in the east and on the boundaries of the city. This pattern is similar for the share of informal employment and residents. This suggests that individuals who live in remote locations usually need to commute to access formal employment, and due to the long time that it takes, they prefer to work in an informal job close to their residence.

When taken together, facts 1 and 2 imply that commuting costs explain to some extent the large informality rates in cities in developing countries. Hence, transit infrastructure that connects informal workers with formal employment can generate additional welfare effects by reallocating workers from the informal to the formal economy. In the next section, I provide evidence of this channel by showing that line B of the subway induced this reallocation.

3.2.2 Difference-in-Difference Specification

Fact 3: *Informality rates decline with transit improvements that improve market access of formal employment to informal workers.*

I now exploit the construction of line B of the subway in Mexico City by estimating a difference-in-difference specification. I compare locations close to the new subway line with the rest of Mexico City and test whether areas close to the new line experienced a change in informality trends after the transit shock controlling for initial characteristics. One feature of this line is that it connected remote locations in the state of Mexico, close to Ecatepec de Morelos, with the center of the city. The identification assumption is that the opening of the new stations is uncorrelated with local demand/supply shocks. The fact that the line was planned decades earlier makes plausible this assumption. Another potential

[17] Figure A3 shows that the labor wedge in these locations is higher.

concern is a change in the composition of 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. Furthermore, in the quantitative framework, I consider this channel by allowing migration within the city. For this exercise, I use both workers' and residents' informality rates as dependent variables.

First, I use the Economic Censuses and estimate the following specification to test whether areas close to the new subway lines experienced changes in workers' informality rates:

$$y_{i,t} = \sum_{\tau \neq 1994} \beta_\tau \mathrm{T}_i + \delta_i + \delta_{s(i),t} + \gamma_t \mathrm{X}_i + \epsilon_{i,t}, \tag{3.2}$$

where $y_{i,t}$ is one of the outcomes of interest of census tract i at moment t. I estimate equation 3.2 for different outcomes that are: the share of informal workers, the share of informal firms, and the log of the number of workers in the informal and the formal sector; T_i is one of four different treatment variables: the log distance in meters, the log distance in walking minutes using the network of roads, 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 a range of 25 minutes; δ_i are census tract fixed effects, and $\delta_{s(i),t}$ are state-time or municipality-time specific trends,[18] $\gamma_t \cdot X_i$ are census tract characteristics-time-specific trends that includes distance controls such as: the area in square kilometers, distance to other stations of public transit, and a central business district dummy variable. $\epsilon_{i,t}$, is the error term of the regression. The coefficients of interests are the parameters β_τ, and the baseline year is 1994. Since the line was built in 2000, the placebo for parallel trends corresponds to 1999. I compute the standard errors with clusters at the census tract level.

Figure 6 and table 2 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 to 4.0 percentage points in locations that experienced the shock. The results are similar using the standard definition of informality or a stricter definition of informality that considers only informal and non-salaried workers that do not have an actual contract with the establishment. Moreover, these effects are robust to the use of the Euclidean distance, the walking distance using the network of roads, or dummy variables indicating whether locations are close to the new stations within some range (i.e., 2000 meters or 25 minutes). Furthermore, in columns five to eight, I include municipality-time fixed effects and the results hold, suggesting that even after comparing locations within the same municipality, census tracts closer to new stations experienced a change in the trend of informality rates after the shock. Finally, in the appendix, I report the results restricting the sample to census tracts with a centroid that is farther than 500 meters from one of the new stations (table B4). The results are similar to the ones in which I include the entire set of locations. I also show that the results are similar if the dummy variable is constructed using a walking range of 20 minutes (figure A5). Overall, the results suggest that informality rates decrease approximately between 5.0 to 8.0 percent after the transit shock, using as a baseline the mean of the outcome in 1999, the period before the construction of line B.

[18] For the municipality fixed effects specifications, I group locations in the state of Mexico in four different groups: North-West, North-East, Middle-West, and Middle-East for a total of 20 municipalities.

Table B3 in the appendix reports the results for the share of informal firms. The results are similar to the ones for the share of informal workers. In particular, after the transit shock, informality rates decrease between 1 to 2.5 pp., which corresponds to a decrease between 2 to 3 percent on informality rates using as a baseline the mean in 1999. There are some issues with parallel trends since there are some small effects for 1999. Finally, when I decompose these effects by studying the response of the total number of informal and formal workers in table B5 and B6, I find that these locations experienced a decrease in the number of informal workers of approximately 1.0 to 1.3 percent, and an increase in the formal labor force of approximately 0.9 percent in 2009.

The previous results show a negative relationship between workers' informality rates and public transit that facilitates commuting. I now test for changes in informality trends in terms of the number of people that live in locations that experienced the transit shock. I use data on the Population Censuses and estimate the following specification relating the change between 2000 and 2010 of the ratio between formal and informal residents with the transit shock:

$$\Delta\left(\ln L_{iF} - \ln L_{iI}\right) = \beta \mathrm{T}_i + \gamma X_i + \delta_{s(i)} + \epsilon_i, \tag{3.3}$$

where L_{is} is the number of individuals that live in i and sector s, and the other parameters represent the same variables as in equation 3.2. This equation relates the log of the ratio between formal and informal workers with the transit shock. Equation 3.3 corresponds to a structural relationship that I will derive in section 5 from the model. This equation will allow me to estimate a labor supply elasticity parameter that governs the reallocation from the informal to the formal economy. I estimate equation 3.3 for the pool of workers and for different groups based on skills. One caveat of this specification is that I can not test for parallel trends due to data constraints because I do not observe the location of informal/formal residents before the 2000 Census.

Table 3 reports the results for different specifications of equation 3.3, while figure 7 depicts the point estimates of my preferred specification for the pool of workers, low-skilled, and high-skilled workers. Overall, the results imply that locations close to the new subway line experienced a decrease in the trend of residents' informality rates. In particular, the ratio of formal to informal individuals increased between 3.0% to 7.6% after the shock. These results are robust to different specifications, for example, to the use of different definitions of the treatment variable, or to include different sets of fixed effects or controls. In addition, in panel C and panel D, I control for the change in the composition of workers in terms of skills, and report the results only considering 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% to 7.5%. The results imply that workers reallocate to the formal sector.

In the next two sections, I test the robustness of my results using an expansion plan from 1980 and show that in terms of observed covariates, there is a negligible change in the composition of households, which is a potential concern of my identification strategy.

3.2.3 Robustness Checks

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 4 plots a map of Mexico City highlighting the three lines that I will compare in this section: Line B, which is the infrastructure project that I'm studying; line C, a feeder line similar to line B that was planned to connect part of the state of Mexico and the North-West with the center of Mexico City, but was never built; and, line 12, which is the latest subway line that was opened in 2012.

I estimate the same difference-in-difference specification from equations 3.2 and 3.3. 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, 1,500 meters), and similarly, the control group are locations within some buffer zone of line C and/or line 12. I run these regressions for three different buffers: 1500, 2000, 2500, and 3000 meters.

Figure 8 depicts the main result from this exercise. I plot the coefficients for the most restricted definition of workers' informality. The main finding is that there is a negative relationship between informality rates and transit improvements when comparing locations that experienced the shock with census tracts close to lines that were planned in the 1980s. For instance, informality rates in terms of workers decrease on average between 4.0 to 11.0 percentage points, which is a larger effect that the one found previously. This effect corresponds to a decrease by approximately 15%, using as a baseline the control group before the shock. In most of the specifications, I also find parallel trends, suggesting that after the shock treated locations experienced the change in informality trends.

In addition, figure 9 depicts the point estimates for the log of the ratio between formal and informal workers from equation 3.3. I find a similar pattern to the previous results. The log of the ratio between formal and informal workers increases approximately 10% when comparing 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 is very stable.

Overall, the main findings are similar if I compare informality trends of the treatment units with all census tracts in Mexico City as in the previous section, or if the comparison is with a more restricted sample of locations close to lines that the Mexico City's Government planned to construct in the 1980s, but that were not built in my period of analysis.

3.2.4 Households' Composition

A potential concern to the identification strategy from the previous section is that locations close to the new subway line might experience a change in the composition of households.[19] 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 is a decrease in informality rates that explain my findings. Ideally, I would deal with this issue is by using a panel of workers before and after the shock that follows the same worker over time. Unfortunately, this panel does not exist in Mexico.

I deal with this threat by comparing household characteristics before and after the shock. The goal is

[19] In the model, I am allowing for changes in terms of un-observed characteristics since it considers migration within the city. However, the model only assumes one type of worker. Because of this, I also analyze changes in households' composition.

to show that at least in terms of observable covariates, there was no change in households' composition. For that purpose, I run the same specification from equation 3.3 with household characteristics such as the high-skill share on the left-hand side.

Table 4 reports the results. I find that on average, household characteristics in locations close to line B didn't vary with the shock relative to other areas in Mexico City. For example, the point estimates for the share of high-skilled workers or the share of students are negative, but not significant. This finding implies that at least in terms of observable characteristics, there is not a change in the composition of households due to the transit shock that can bias my estimates.

This result is similar to what other papers have found in the Mexican context. For example, Gonzalez-Navarro and Quintana-Domeque (2016) exploits 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.

4 Model

In this section, I present a quantitative model to assess the aggregate welfare effects from transit improvements that considers first-order effects on allocation. The model is based on recent work by Tsivanidis (2019), Monte et al. (2018), Heblich et al. (2018), and Ahlfeldt et al. (2015). Relative to their work, my model extends these models by adding inter-sectoral wedges and resource misallocation.

The main theoretical result is a formula from a first-order approximation, that decomposes the total change in welfare after a transit shock into three different components: a "direct" effect term, and an allocation term that can also be decomposed into two components: a resource misallocation effect, and an agglomeration externality term when these forces differ between the two sectors. This formula is similar to the general case from Baqaee and Farhi (2019) in GE models on changes in productivity that follows the seminal paper by Hulten (1978).

In the model, I assume that there are three groups of agents in the economy: workers denoted by L, house owners represented by H, and commercial floor space owners denoted by Z.[20]

4.1 Preferences

There is a mass of $\mathcal{N}$ locations in the economy 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 sector 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

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

where C represents consumption, H housing, the parameter α represents the expenditure share on

[20]The main interest of the paper is efficiency. In the appendix, I generalize the results to consider different group of workers such as high and low skilled. Intuitively, the results are isomorphic if preferences for the formal and informal sector come from the scale parameters of the Fréchet shocks, or if the commuting and labor supply elasticities differ between the two groups, and low-skilled workers have preferences to work in the informal sector.

the consumption good, d_{ni} is an iceberg commuting cost to move from location n to i, and ϵ is an idyosincratic shock of 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

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

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 rebate from the government after collecting taxes. The term $\epsilon_{nis\omega}$ is an idiosyncratic utility shock that is drawn from a nested Fréchet or extreme value type II distribution $H(\cdot)$,[21]

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

Each worker receives a one-time shock and makes three decisions, one for each nest: 1) where to reside, 2) the sector to work, and 3) the workplace. The parameters η, κ, and θ_s measure productivity dispersion across locations, sectors, and workplaces respectively and capture the notion of comparative advantage in terms of migration, and productivity for sectors and locations.[22] On the other hand, the parameters B_n capture specific amenities that attract residents for each location n. I assume that these parameters are fixed over time.

I allow that the third parameter θ_s differs across sectors to capture the fact that productivity differences across locations are larger in the formal sector. This parameter also represents the labor supply elasticity with respect to commuting cost conditional on working in sector s. I expect that in the estimation $\theta_F < \theta_I$, which implies that workers in the informal sector are more sensitive to commuting costs, and thus, 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

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

where $W_n^{\kappa} = \sum_{s'} W_{ns'|n}^{\kappa}$ is a wage index from location n, and $W_{ns|n}^{\theta_s} = \sum_{i'} w_{is}^{\theta_s} d_{ni'}^{-\theta_s}$ 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, the probability of living in n; second, the probability of working in s 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

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

[22] 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 last 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.

$\sum_i \lambda_{nis|ns} = 1$, $\sum_s \lambda_{ns|n} = 1$, and $\sum_n \lambda_n = 1$.

Using again the properties of the Frechet distribution, I equate the expected ex-ante utility of a worker to the following constant:

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

where γ_η is a constant term.[23] Then, 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 received by workers that reside in n is $\bar{y}_n \equiv \sum_{i,s} \lambda_{nis} w_{is}$. I now explain in more detail the assumptions and market structure of the composite good.

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. 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 within each sector:[24]

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

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, then, as a consequence agglomeration externalities differ between the two sectors generating an additional allocation effect. In principle, we should expect that $\sigma_F < \sigma_I$ to capture that trade flows in the informal sector are more sensitive to trade costs and that agglomeration externalities are larger in the formal sector. I will estimate these parameters by estimating gravity equations. The price index P_n in location n, and the price indices for each sector P_{ns} take the usual 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 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

[23]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 Frechet distribution.

[24]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).

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:

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

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 am adding 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 generating dispersion in TFPR and then lowering TFP.

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

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

The zero profit condition implies that the equilibrium output of each variety is constant across firms that operate in the same location and sector 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 and $1-\beta$ respectively:[25]

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

From these expressions, I can construct the labor demand.

4.2.1 Expenditure shares

The assumption of CES preferences implies a standard gravity relationship for bilateral trade flows in goods between 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

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

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. Finally, 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 in each location i and sector s in equilibrium is a function of the aggregate amount of labor and commercial floor space:[26]

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

where $\tilde{\beta} \equiv \beta^{-\beta}(1-\beta)^{-(1-\beta)}$ is a constant term. The fact that consumers have a love of variety (LOV) and that there is free-entry imply that there are agglomeration forces for each sector. As mentioned above, these agglomeration forces have 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 as in Bartelme et al. (2019).

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 ($\tau_{ni\tilde{H}} = \tau_{ni\tilde{Z}} \to \infty \quad \forall n \neq i$) and operate under perfect competition in all locations. The only factors of production of these sectors are the group of agents H, and Z. The former supplies units to residential housing, and the latter to commercial floor space. The production function for both sectors is linear in labor and given by:

$$\tilde{H}_i = \tilde{L}_{iH} \tag{4.12a}$$

$$\tilde{Z}_i = \tilde{L}_{iZ}. \tag{4.12b}$$

There is no commuting for both groups, therefore, they only supply units where they live, which means that $d_{niH} = d_{niS} \to \infty \quad \forall n \neq i$. The indirect utility of worker ω from group ν where $\nu \in \{H, Z\}$ to live in location n is:

$$\bar{U}_{n\nu\omega} \equiv \frac{B_n w_{n\nu} \cdot \epsilon_{n\nu\omega}}{P_n^{\alpha} \cdot r_n^{1-\alpha}}, \tag{4.13}$$

where $\epsilon_{\nu\omega}$ is an idiosyncratic shock drawn from a Frechet distribution with dispersion parameter η_ν, and location parameter $T_{i\nu}$, $w_{n\nu}$ is the wage per efficiency unit of group ν in location n. I assume that

[26] 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 $A_{is} = \tilde{A}_{is} \cdot \tilde{L}_{is}^{\beta\gamma_s} \tilde{S}_{is}^{(1-\beta)\gamma_s}$, where $\gamma_s = \frac{1}{\sigma_s - 1}$.

$\eta_\nu \to 1$, where $\nu \in \{\tilde{H}, \tilde{S}\}$, this assumption replicates the specific factor case. Then, the supply of residential and commercial floor space is perfectly inelastic and is fixed. Finally, from the production function of housing and the assumption of perfect competition, the price of housing in location n is $r_n = w_{nH}$, and the price of floor space, $q_i = w_{iZ}$.

Using equation 4.9, which relates payments to labor and commercial floor space in terms of total revenue from (i, s), the equilibrium condition to clear the market of commercial floor space in each location i is:

$$q_i \tilde{Z}_i = \sum_s \frac{(1-\beta)(1+t_{isL}) w_{is} \tilde{L}_{is}}{\beta(1+t_{isZ})}, \tag{4.14}$$

this equation equates the supply of commercial floor space described by the left hand side to the demand by firms that is described by the right hand side. Similarly,the housing market clearing condition is:

$$r_n \tilde{H}_n = (1-\alpha) X_n, \tag{4.15}$$

where X_n is total expenditure from location n, which I will explain later. This expression equates the total supply of housing to total demand.

4.4 Government Budget Constraint

As mentioned above, 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:

$$\sum_{i,s} \left(t_{isL} w_{is} \tilde{L}_{is} + t_{isZ} q_i \tilde{Z}_{is} \right) = \bar{t} \cdot \sum_n X_n. \tag{4.16}$$

This equation equates the income of the government from the left-hand side to total expenditure on the right-hand side. I proceed to close the model by finding an expression of total expenditure in each location.

4.5 Goods and labor market clearing

I now derive the equilibrium conditions for goods market-clearing. I first analyze the expression for total expenditure from location n, and then, 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, the total expenditure from location n is given by the following expression:

$$X_n = (\bar{y}_n L_n + q_n Z_n + r_n H_n)(1+\bar{t}). \tag{4.17}$$

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}, is given by:

$$Y_{is} = \alpha \sum_{n} \pi_{nis} X_n. \tag{4.18}$$

Finally, equating labor demand and labor supply, the goods market clearing condition to close the model is:

$$w_{is}(1 + t_{isL})\tilde{L}_{is} = \alpha\beta \sum_{n} \pi_{nis} X_n. \tag{4.19}$$

This equilibrium condition implies that total payments to workers including taxes is equal to a fraction β of total revenue, where total revenue is 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:

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

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 4.17; goods market clearing described by equation 4.19; commercial floor space market clearing described by equation 4.14; housing market clearing described by equation 4.15; labor market clearing; and the government budget constraint from equation 4.16.

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 forces should be lower than congestion forces. The parametric condition is:

$$(1 - \alpha) > \frac{1}{\sigma_s - 1} \ \ \forall s.$$

I proceed to analyze the effect of transit shocks on welfare using a first-order approximation.

4.7 Welfare Decomposition

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

$$\bar{U} = \left(\omega_L \bar{U}_L + \omega_H \bar{U}_H + \omega_S \bar{U}_S\right), \tag{4.20}$$

where ω_g represents the weights that replicate the efficient allocation of the economy.[27] This equation suggests that aggregate welfare is a weighted average of the ex-ante utility of the three different types of agents in the economy.

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 $\mathcal{L}$. I'm interested in the effect of shocks on aggregate welfare assuming that the initial equilibrium is perfectly efficient. By a first order approximation, the total change in welfare of any trade/commuting shock is:

$$d \ln \bar{U} = \underbrace{\frac{\partial \ln \bar{\mathcal{U}}}{\partial \ln A} d \ln A}_{\text{“Direct” effect}} \quad + \quad \underbrace{\frac{\partial \ln \bar{\mathcal{U}}}{\partial L} dL}_{\text{Allocation/Agglomeration}} \quad . \tag{4.21}$$

Equation 4.21 suggests that the effect of any shock can be decomposed in two different terms: a direct effect term that considers just changes in exogenous parameters as iceberg commuting costs d_{ni} or trade costs τ_{ni}, and a first-order allocation term. This second term captures allocation from two different forces: wedges and differences in agglomeration externalities between the two sectors.[28] [29]

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

$$\text{“Direct” effect} = -\alpha\beta \sum_{n,i,s} \lambda_{nisL} \cdot d \ln d_{ni} - \alpha \sum_{n,i,s} \left(\beta\lambda_{nL} + (1-\beta)\lambda_{nZ}\right) \pi_{nis} \cdot d \ln \tau_{ni} \tag{4.22a}$$

$$\text{Allocation} = \alpha \left(\beta \sum_{n,i,s} \left(\frac{t_{isL} - \bar{t}}{1+\bar{t}} \right) \lambda_{nisL} \cdot d \ln \tilde{L}_{nis} + (1-\beta) \sum_{n,s} \left(\frac{t_{nsZ} - \bar{t}}{1+\bar{t}} \right) \lambda_{nsZ} \cdot d \ln \tilde{Z}_{ns} \right) \tag{4.22b}$$

$$\text{Agglomeration} = \sum_{i,s} \frac{\beta}{\sigma_s - 1} \left(\frac{1+t_{isL}}{1+\bar{t}} \right) d\tilde{L}_{is} + \sum_{i,s} \frac{(1-\beta)}{\sigma_s - 1} \left(\frac{1+t_{isZ}}{1+\bar{t}} \right) d\tilde{Z}_{is}. \tag{4.22c}$$

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 share of people who live in location n, and the share of people that commute to i.[30] This is the cost-saving formula used by Train and McFadden (1978) to evaluate reductions in commuting costs. This implies that if the goal is to understand the aggregate gains, in the case in which the shock to commuting costs is very small, all the nominal effects of prices such as wages and labor cancel out.

The second term captures changes in allocative efficiency. It suggests that if workers reallocate to sectors-locations with higher wedges, there is an increase in welfare. Hence, changes in commuting costs may have an additional first-order impact in the presence of distortions. Intuitively, the sign

[27] 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 $\frac{\omega_H \bar{U}_H}{\bar{U}} = (1-\alpha)$.

[28] The agglomeration externality component captures distortions from differences in *markups* or differences in preferences for love of variety across the two sectors.

[29] This formula applies in the general class of urban models for any wedge. For example, variable market power across firms in product or labor markets. In the appendix, I show this result for any kind of wedge.

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

depends on whether workers reallocate to firms with larger wedges. Firms that pay higher taxes 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 improving allocation.

Finally, the last term represents agglomeration forces. This component only arises in the presence of externalities that differ between the two sectors as in BCDR or trade imbalances as in FG. This term captures the effect of these externalities on aggregate TFP and welfare. In my case, agglomeration externalities differ between the two sectors, and wedges and transfers create trade imbalances, so the third term also shows up in the formula. This component depends on two forces: 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. Conditional on productivity, firms that are paying higher taxes are very small due to trade imbalances, then reallocating workers to these firms increases welfare.

I show the derivation of this formula in section D.2 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 D.3. The only assumptions for this derivation are that the utility function, production function, the consumption good aggregator, and the efficiency units aggregator are homogeneous of degree one.[31]

Most of the literature which primarily interest has been to measure the welfare gains from transit infrastructure has focused on the first term and direct effects, assuming that there are no wedges in the economy and that it operates under perfect competition. I contribute to this literature by analyzing the effect of transit improvements on the second and third margin. The main hypothesis is that transit improvements have an additional impact on efficiency by reallocating workers to the formal sector, which is the sector with larger wedges and higher agglomeration externalities. Since this formula applies for 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 percentage changes and exact hat algebra.

In the next section, I proceed to estimate the main parameters of the model and to quantify the effect of the second and third terms after the construction of the line B of the subway.

5 Empirical Strategy and Estimation

In this section, I describe the main empirical strategy and estimation of the main parameters. This section is divided in four parts: parametrization of commuting and trade costs; estimation of trade and commuting elasticities; estimation of the labor supply elasticity across sectors -κ-, which is the parameter that governs the reallocation from the informal to the formal sector; and model inversion to recover the fundamentals of the economy such as technological and amenity parameters.

[31] In addition, in section D.6 of the appendix, I show a formula for this welfare decomposition using percentage changes based on Holmes et al. (2014) and Asturias et al. (2016).

5.1 Trade and Commuting Costs

For the counterfactual analysis, I parametrize commuting costs as in the urban economics literature (Ahlfeldt et al., 2015; Heblich et al., 2018; Tsivanidis, 2019). I assume that both iceberg commuting and trade costs are parametrized using the following expressions:

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

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

where time_{ni} is the average travel time in minutes across different transportation modes of moving from location n to location i. The main objects of interest are the parameters δ_d, and δ_τ that transform travel times to iceberg costs. I estimate these parameters from a Nested Logit specification using the 2017 Origin-Destination survey. I use trips to from their home to their work and vice-versa to estimate δ_d, and trips to restaurants, outlets, and retail shops to obtain the parameter δ_τ.

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

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

where $V_{nim\omega}$ is the indirect utility of worker ω if he/she chooses transportation mode m to travel from n fo i. This is the classic framework that Berry (1994) studies. The parameter δ measures the sensitivity of the decision of the worker/consumer to the average time she spends on moving across locations. The parameter γ_m captures preferences for transportation mode m relative to a baseline mode; in my case, I normalize γ_{walking} to zero. For example, γ_{car} captures preferences for car relative to walking, this can include the price of a car, or the stress of driving in a complicated city such as Mexico City. 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 logit case. Finally, $\epsilon_{nim\omega}$ is an idyosincratic shock of worker ω of choosing m. The error term of this equation is $\psi_{nig\omega} + (1 - \lambda_g)\epsilon_{nim\omega}$ which is drawn from an Extreme Value type I distribution.

Table 5 shows the main result after estimating the nested logit specification. The first column reports the results for commuting, and the second column reports the results for trade trips. I obtain a value for δ_d of 0.010, which is consistent with previous findings from the literature (Ahlfeldt et al., 2015). The point estimate for δ_τ is 0.012, which, while a bit large, is similar to what Tsivanidis (2019) finds in the case for commuting in Bogotá, a similar context to Mexico City. On the other hand, in terms of preferences, when people go to work, the most preferred transportation mode is car, while if they travel to restaurants or retail shops, they have more preferences to walk. The last two rows report the average iceberg commuting and trade costs across locations in Mexico City before and after the transit shock. On average, after line B of the subway opens, commuting costs drops by 9.00%, and trade costs drops by 11.13%

5.2 Commuting and Trade Elasticities

Commuting Elasticities: To estimate the commuting elasticities, I use the Intercensal 2015 survey. In this survey, workers report the municipality of their residence and workplace, and I am also able to define formal and informal workers using employment and social security information. From the model, it is easy to derive the following gravity equation relating commuting flows across municipalities and iceberg costs:

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

where the subindex m corresponds to one of four different transportation modes: car, metro or metrobus, bus, and walking; $\lambda_{nism|ns}$ is the share of workers that commute to location i from location n working 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 the measurement error observed in the data of this gravity equation.

The goal is to recover the parameters θ_s after knowing β_s and δ_d described in the previous section. The parameter θ_s captures how sensitive workers are to commute in the formal/informal sector. From the evidence in section 3, the expected result is that $\theta_I > \theta_F$, suggesting that informal workers respond more to commuting costs than formal workers since they work closer to their home. 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 workplace decision of workers 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 6 reports the results. As expected, there is a negative relationship between commuting flows and the average commuting times. I find that the commuting elasticity in the formal sector is 3.3, and in the informal sector it is approximately 4.4. These values are consistent with the theoretical assumptions, and they confirm that informal workers are more sensitive to commuting costs than formal workers.

Trade Elasticities: To estimate the trade elasticities, I use the 2017 OD survey focusing on data on trips to different establishments. I restrict the sample to trips to restaurants, retail shops, and factory -outlets. I assume that people move across the city and spend their income on different consumption goods. To estimate a different trade elasticity for the informal and formal sector, I use the fact that most of informal establishments in Mexico correspond to restaurants and retail shops, while most of formal establishments are manufacturers, as figure 10 shows (Levy, 2018). Similar to the commuting case, I estimate the following gravity equation relating trade flows $\pi's$ across municipalities -trips- with iceberg trade costs:

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

where the different parameters represent the same variables as in equation 5.2. In this case, the identification comes from comparing trips to locations that use the same transportation mode and which origin (destination) is the same, but in which individuals are moving to (from) a different municipality. I estimate this equation via PPML to include zero trips across locations. The goal is to recover the parameters σ_s. These parameters represent the elasticity of substitution across varieties and capture the trade elasticity for each sector. They measure how sensitive trade flows are to trade costs when people move across the city to buy different goods. In addition, according to the monopolistic model, they also represent agglomeration externalities given by $\frac{1}{\sigma_s - 1}$. These forces show up in the model because consumers have preferences for "Love of Variety" and free-entry. As in BCDR, I allow these externalities to differ by sector, generating additional welfare effects from workers' reallocation. One expected result is that $\sigma_I > \sigma_F$ indicating that agglomeration forces are larger in the formal sector. The intuition for this result is that informal varieties are more substitutable than formal ones, and as a consequence, agglomeration forces in the informal sector are lower.

Panel B in table 6 describes the main results for this exercise. As in all gravity equations, trade flows decrease with commuting times. The estimate of σ for both sectors is low, but it is consistent with the results from the previous literature. In particular, the elasticity of substitution in the informal sector is 5.2, and in the formal sector it is 4.0, suggesting that agglomeration externalities are 0.24 in the informal sector, and 0.33 in the formal sector. One caveat from these findings is that these externalities are relatively large compared to the previous findings in the literature which is around 0.1-0.2. However, both numbers are still reasonable, especially in the developing world.[32] In the next section, I estimate the key parameter of the model, the labor supply elasticity across sectors using a log-linear relationship.

5.3 Labor Supply Elasticity-Sectors

In this section, I estimate the main equation from the model to recover κ. This parameter corresponds to the labor supply elasticity across sectors that governs the reallocation of workers from the informal to the formal economy. I build market access measures following Tsivanidis (2019). According to the model, these measures represent the wage index for each sector. Hence, they capture whether workers obtained better access to formal jobs relative to informal jobs after the transit shock.

For this exercise, I calculate travel times across the different census tracts in Mexico city with and without line B of the subway using the network analysis toolkit from Arcmap. I compute travel times for three different transportation modes: car, walking, and the public transit system. 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.[33]

[32] Tsivanidis (2019) find that agglomeration forces in Bogota, Colombia are 0.21 which is a larger value than previous findings.

[33] Section C1 in the appendix explains the procedure.

With the commuting times at hand and following the recent literature, I define the commuter market access (CMA) for location n and sector s as

$$\text{CMA}_{ns} \equiv \sum_i w_{is}^{\theta_s} d_{ni}^{-\theta_s}.$$

This is an index of the accessibility of jobs in location n to employment in sector s. It captures whether workers that live in n have good access to jobs from sector s. Following Tsivanidis (2019) and Donaldson and Hornbeck (2016), I can solve the following system of equations to compute MA measures for both firms and commuters specific to each sector and location:

$$\text{CMA}_{ns} = \sum_i \frac{\tilde{L}_{is} d_{ni}^{-\theta_s}}{\text{FMA}_{is}} \tag{5.4a}$$

$$\text{FMA}_{is} = \sum_n \frac{L_{ns} d_{ni}^{-\theta_s}}{\text{CMA}_{ns}}, \tag{5.4b}$$

where $\tilde{L}_{is}$ represents the total amount of labor hired by location i and sector s; L_{ns} corresponds to the total number of workers that reside 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. Tsivanidis (2019) 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 5.4b has a unique solution.[34]

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 in the sector in which workers operate. Figure 11 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 12 plots the change in CMA, taking the difference between the formal and informal sector and considering differences in the commuting elasticity across sectors. The figure shows that census tracts near line B experienced a larger increase in market access in the formal sector. As a consequence, 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 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, and similar to the reduced-form results from section 3, I can estimate the following labor supply equation that relates changes in the ratio between formal and informal residents with the change in CMA measures

[34] 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 to solution, up to scale to this system of equations.

over time and across sectors:

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

where Δ corresponds to the 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 sector respectively; $\gamma_{s(n)}$ 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. Equation 5.5 is a labor supply relationship and implies that people reallocate to the formal sector as they obtain better access to formal jobs relative to informal employment. As figure 12 shows, Line B improved the access to formal jobs for residents close to line B. My main hypothesis is precisely that locations near line B of the subway experienced an improvement in access to formal jobs relative to formal jobs.

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. These shocks can change the decision of workers to operate in the formal or informal sector generating correlation between the change in CMA and the error term. This generates a bias in the estimation of κ. To deal with this problem, I estimate equation 5.5 by two stage least squares using two instruments. The first instrument is the change in the CMA measures holding the number of residents and workers fixed. The idea is to capture changes in commuting costs and clean the estimation from other shocks in the economy by holding $\tilde{L}_{is}$, and L_{ns} constant. The second instrument corresponds to the dummy variables from equation 3.3, in particular whether the centroid of the census tract is within a 25 minutes walking range. Similar to the previous instrument, the goal is to capture changes in the CMA explained only by the transit shock of line B.

Table 7 reports the results for the labor supply elasticity across sectors. I obtained estimates of κ between 1.1 and 1.7. These estimates are consistent with the model and the commuting elasticities. 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 specification, which is the one in column 6, that includes municipality fixed effects and uses as an instrument the dummy variable, I obtained an estimate of 1.70. 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 moving workers from the informal to the formal sector and generating a negative correlation between the change in the CMA measures and the error term. [35] Relative to previous literature such as -Galle et al. (2017), Lagakos and Waugh (2013), and Berger et al. (2019)- that has also focused on estimating labor supply elasticities across sectors, my estimates are a bit lower, but they are consistent with the theoretical assumptions. For the counterfactuals, I will use an estimate of $\kappa = 1.5$ by taking an average across specifications.

The point estimate of κ implies that while any shock that improves wages in the formal sector

[35] I didn't instrument the change in CMA with the two instruments since both of them capture changes in commuting cost because of the transit shock.

relative to the informal sector net of commuting costs reallocates workers, the responses are actually very small. A value of $\kappa = 1$ replicates the specific factor model in which workers do not move across sectors. As a result, only big commuting shock that improve market access in the formal sector can generate significant additional welfare gains through the allocative efficiency channel, which is the mechanism that my paper studies.

5.4 Labor Wedges

Labor wedges are a crucial parameter for the quantitative analysis. I follow the popular approach from Hsieh and Klenow (2009) and use the inverse of the wage bill share to calibrate labor distortions.[36] 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. From the profit maximization condition, the inverse of the labor share paid by each firm is

$$\left(\frac{w_{is}l_{is}}{p_{is}y_{is}}\right)^{-1} = \underbrace{\frac{\sigma}{(\sigma-1)\beta}}_{\frac{1}{1+\bar{t}_L}}(1+t_{isL})$$

where $w_{is}l_{is}$ is the wage bill, and $p_{is}y_{is}$ are total sales or value-added. I can observe the left-hand side of this equation for each firm in the Economic Census, and use the average labor share β in each industry to calibrate labor wedges. To aggregate from the firm level to the census-tract-sector cell, I take the median of the inverse of the wage bill share across firms in each cell.

Figure 14 plots the labor wedge distribution across locations for each sector in the baseline year. The estimates between the formal and informal sector 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 1.6 times the wedge in the informal sector. Furthermore, figure A3 in the appendix shows the spatial distribution of labor wedges after constructing ventiles across locations. In places in the center of the city, where there is more economic activity and formal firms locate, wedges are larger. This calibration implies that conditional on productivity, formal (informal) firms are too small (big) relative to the perfectly efficient allocation.

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, on average, a value of $\alpha = 0.61$. Similarly, for the labor share, I use data from the Economic Census in 1999 and find a value of $\beta = 0.70$. To calculate the total amount of housing $\tilde{H}$ and commercial floor space $\tilde{Z}$ in each location, I use the area in square kilometers of buildings in each census tracts from Open Street Maps 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 workforce in each sector from the model

[36] Another option to calibrate the labor wedge is to use social security information. However, this is more complicated since these payments may capture other forms of salary, and social security payments may not represent different types of wedges between the informal and the formal sector such as output taxes.

finding $F_I = 0.15$, and $F_F = 1.2$. Section C.2 in the appendix specifies the details for this estimation. This result is consistent with the fact that for a firm, it is more difficult to produce in the formal sector. In addition, I use the estimate of the elasticity of substitution across sectors $\xi = 1.24$ from Edmond et al. (2015), which is similar to the estimates of other papers (Asturias et al., 2016). Also, I compute the counterfactuals using a value of $\eta = 1.50$ which is the lowest value of the migration elasticity that Tsivanidis (2019) finds for Bogotá, which is a similar context to Mexico City. This value is consistent with the assumption that $\eta \leq \kappa$ from the theoretical framework and the value of κ that I found in the previous section.

5.6 Model Inversion

In this section, I recover the fundamental parameters B_{ns}, which capture differences in amenities that attract residents to each location and sector; and the parameters A_{is}, which represent differences in productivity across location. The argument is that knowing the key elasticities, the number of workers and residents in each location and sectors, and the distribution of wages, I can identify the entire model from section 4. Knowing these parameters, I can then compute trade flows and commuting flows and solve the counterfactuals using initial equilibrium conditions and the elasticities from previous sections.

I proceed in three steps. In the first step, I use CMA measures to recover relative differences in amenities across sectors for each location. The second step uses FMA measures to recover the wage distribution across locations for each sector, and in the third step, I recover the productivity levels A_{is} by solving the model and holding constant the number of residents constant. Finally, I can obtain the initial commuting and trade flows and use hat algebra for the counterfactuals, and recover the parameters B_n by solving the migration conditions equating the predictions of the model with the data.

Step 1: I parametrize the amenity parameters B_{ns}, without loss of generality assuming that $B_{nF} = B_{nI} \times b_{nF}$. From the CMA measures derived in the previous section, I can identify b_{nF} from the following relationship:

$$\frac{L_{nF|n}}{L_{nI|n}} = \frac{b_{nF}\mathrm{CMA}_{nF}^{\frac{\kappa}{\theta_F}}}{b_{nF}\mathrm{CMA}_{nF}^{\frac{\kappa}{\theta_F}} + \mathrm{CMA}_{nI}^{\frac{\kappa}{\theta_I}}}.$$

This expression implies that the share of residents that work in the formal sector relative to the informal sector in location n is a function of the amenity parameters b_{nF} that represent the relative preferences of workers between the formal and informal sector, and the CMA measures that are a wage index in each sector. Using the variation in the ratio that is not explained by the CMA measures allow me to identify the terms b_{nF} by perfectly fitting the rate of formal to informal workers from the model with the data in each location.

Step 2: I can obtain the spatial and sectoral wage distribution from FMA measures and the total number of workers. According to the definitions of market access:

$$\tilde{L}_{is} = w_{is}^{\theta}\mathrm{FMA}_{is}.$$

By inverting this expression in terms of w_{is}, I can recover the entire distribution of wages. While I observe wages from the Economic Censuses, it is better to use wages derived from the previous expression for three main reasons. First, the data on salaries from the census data do not correspond to wages per efficiency unit of labor as in the model. These wages capture other variables such as differences in education or hours of work that can vary across sectors and locations, and as a result, may generate biases in the wage distribution. Second, labor payments in the data only reflect the monetary compensation of labor, and do not capture other ways in which employers can pay their workforce. And third, one characteristic of informal firms is that they do not report the salary of workers since they pay them with cash "under the table". Figure 13 plots the distribution of log wages across locations for each sector derived from the previous equation. The model replicates very well the fact that formal firms pay higher wages per efficiency unit of labor than informal firms. According to these estimates the average wage premium in the formal sector is approximately 55%.

Step 3: With data on wages, holding constant the number of residents in each location, and knowing the key elasticities, and the other parameters of the model, I can obtain the productivity parameters A_{is}.

The argument in this step is the following: after knowing the wage distribution and the number of residents in each location, I compute commuting flows using workplace and sector choice probabilities from equation 4.2. With these elements in hand, I can build the total number of labor efficiency units supplied for each location. On the other hand, to compute the labor demand, and recover the productivity parameters A_{is}, I solve the goods equilibrium condition from equation 4.19. As a result, I can compute trade flows for each sector across the city and solve for the counterfactuals using exact hat algebra as in Dekle et al. (2008). In section D.5 of the appendix, I provide the equilibrium conditions of the model with exact hat algebra.

6 Counterfactual Analysis

This section describes the counterfactual analysis. To compute the welfare effects of line B, I use the estimates of the key elasticities, and the commuting times with and without line B. Then, I solve for the GE equilibrium before and after the shock.

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, so the total number of workers $\bar{L}$ is constant. 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, assuming a different value of σ_s in the two sectors.

Table 8 reports the results and figure 15 plots the results. Panel A holds the number of residents constant, while panel B adds the migration margin decision. Overall, the results between the two panels are similar. On average, line B of the subway increased welfare by 1.3%-1.6%. Both changes in commuting and trade costs account for around 50% of the total gains. In terms of the welfare decomposition, I find that in the case in which there is no migration the "direct" effect term represents approximately 75% of the total gains, the reallocation of workers to the formal sector explains 17%, and the agglomeration externality component drives the remaining 8%. As a result, the allocation mechanisms generated 33.3% additional gains than the standard case under the perfectly efficient economy. On the other hand, in the case in which I allow for migration in the model, the direct effect a larger fraction of the total gains, 83%; the change in factor allocation explains 14%, and differences in agglomeration externalities between the two sectors 3%.

Relative to the previous literature, and considering the size of my shock, these estimates are a bit larger. Nevertheless, these studies only considered changes in commuting costs and the direct effect. In my counterfactual, I'm analyzing changes in trade costs and the new allocation margin which explain that the welfare effects are bigger.

The cost-benefit analysis of the project implies that in the case of no-migration there was an increase of 0.60% in real income net of cost in Mexico City after the transit shock, and in the case of migration of 0.86%. I obtained this number by taking the difference between the change in welfare and the total cost. In table 9, I report the total cost of the project in net present value and their different components. According to official documents from the Government, the total cost of line B in 2000 was approximately USD 2,900 million dollars in 2014 taking into consideration the net present value of maintenance, operation services, and other overheads. This represented approximately 0.72% of the total GDP of Mexico City in 2000. Then, in the benchmark case (migration) line B generated an increase of approximately USD $201 per capita net of cost at 2014 USD prices. This change would have been only $145 without considering the allocation mechanism. As a result, line B generated an additional increase in total welfare per every dollar spent of approximately 20%.[37] 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 significantly smaller.

The main takeaway from this analysis is that when policymakers assess the economic impact of transit infrastructure, it is critical that they consider other mechanisms that may affect welfare beyond common factors such as transportation demand, which is the typical approach in the cost-benefit analysis of infrastructure. For example, when governments decide where to allocate future infrastructure, they should not only focus on connecting poor areas with efficient locations for distributional implications, but also for efficiency reasons. As this study shows, connecting informal workers with formal employment may generate additional welfare gains by reducing resource misallocation, especially in the developing world. According to my results, there is a substantial increase in welfare if governments improve market access in the formal sector to informal workers.

Other policies

In this section, I consider the effectiveness of other policies that the government can implement to reduce informality. In particular, I study two different types of policies. The first type consists of reductions in the entry fixed costs of formal firms. These policies are akin to make it easier for entrepreneurs to start a formal business in Mexico City (i.e., reducing bureaucracy). On the other hand, the second

[37] This number is obtained in the following way: In the perfectly efficient economy, the total gains are: 1.31% of the GDP, then the benefit per every dollar spent on the project is 1.82 (1.31/0.72). On the other hand, under the inefficient economy, the benefit is 1.58%, this represents that the benefit per every dollar spent on transit infrastructure is 2.19 (1.58/0.72). Thus, there was an increase of 20.3% relative to the perfectly efficient economy.

type of policy considers an increase in the entry fixed cost of informal firms. These policies can be thought of as an increase in government regulations that make it more difficult for informal firms to enter the market.

According to the reduced form estimates, line B of the subway led to a decrease in informality rates at the aggregate level by 2% for both jobs and residents in location. Figure 16 plots the effectiveness of different policies that change the entry fixed cost for both formal and informal firms. Panel a plots the results for different rates decreasing the formal fixed cost, and panel b simulates an increase in the informal entry fixed cost for different rates.

There are three main takeaways from this analysis. First, according to the model, it is more effective to reduce the entry fixed cost of formal firms relative to increasing the entry fixed cost of informal firms. For example, to decrease informality rates by 2% at the aggregate level, the government can lower the formal fixed cost by 25%, but it needs to increase the informal fixed cost by more than 40%. This suggests that it is more effective to focus on policies that benefit formal firms than harm informal firms. Second, as the target of the Government increases, it becomes more effective to reduce the formal fixed costs relative to increasing the informal fixed cost. This second result comes from the fact that the first type of policies are concave in the rate in which the government reduces the formal fixed cost, while the second type is convex in the increase rate of the informal fixed cost. This means that as the objective target to reduce informality increases, reducing the formal fixed costs becomes more effective while increasing the informal fixed cost more ineffective. Third, the results suggest that transit infrastructure that connects informal workers with formal employment can be a useful tool to reduce informality rates. For example, if the government wants to generate similar results at the aggregate level, it needs to reduce the formal fixed cost by 25% or increase the informal fixed cost more than 40%. Overall, these results imply that transit lines can be an excellent tool to reduce informality rates by giving better access to formal jobs to workers that live in remote areas compared to other types of policies that the government may implement.

7 Conclusion

This paper has examined the welfare gains from transit improvements in developing countries, taking into account the allocation margin. The mechanism that it studies is whether workers reallocate from the informal to the formal sector. Informality rates are very high in the developing world. The presence of the informal economy creates wedges that lowers aggregate productivity. I find that transit infrastructure that facilitates commuting in the developing world 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 center of the city. The main finding is that informality rates in terms of both workers and residents decrease approximately by 4.0 percentage points in locations that experienced the shock. This result implies that workers reallocated to firms with higher TFPR, thereby increasing welfare to a larger extent than the predictions under a perfectly efficient economy.

On the theoretical side, the paper departs from the standard efficient case in urban models that has studied the economic impact of transit infrastructure. The model extends the classic framework by adding wedges and resource misallocation. The theoretical contribution is to provide a formula that decomposes the welfare gains of any trade/commuting shock into a direct effect, a resource misallocation term, and an agglomeration externality component. I estimate the key elasticities by using variation in commuting and trade flows across census-tracts in the cross section, and by exploiting the change in informality rates using the transit shock. The paper quantifies the gains from transit infrastructure findi/ng that allocative efficiency drives approximately 17%-25% of the total gains.

The results from this study are informative to policy-makers in several aspects. First, it is critical that when authorities analyze the cost-benefit and opportunity cost of a project, they take into consideration other first-order effects that are not just driven by direct effects through the classic approach of transportation demand. These projects can have an additional economic impact through an allocation margin. For example, they should consider whether the population that resides in potential connected areas work in the informal or formal economy. The paper shows that even if a government is not concerned about distributional aspects, connecting poor areas with high efficient locations can generate larger welfare gains than transit developments that link locations with a similar composition of workers through this new margin.

Moreover, the results are informative in other public policy issues in urban areas. Programs that segregate informal workers and poor individuals in cities in developing countries combined with the high commuting costs can increase the extent of resource misallocation, lowering both aggregate efficiency and TFP. Hence, Governments must make decisions based on an analysis that considers all the components that may affect aggregate welfare.

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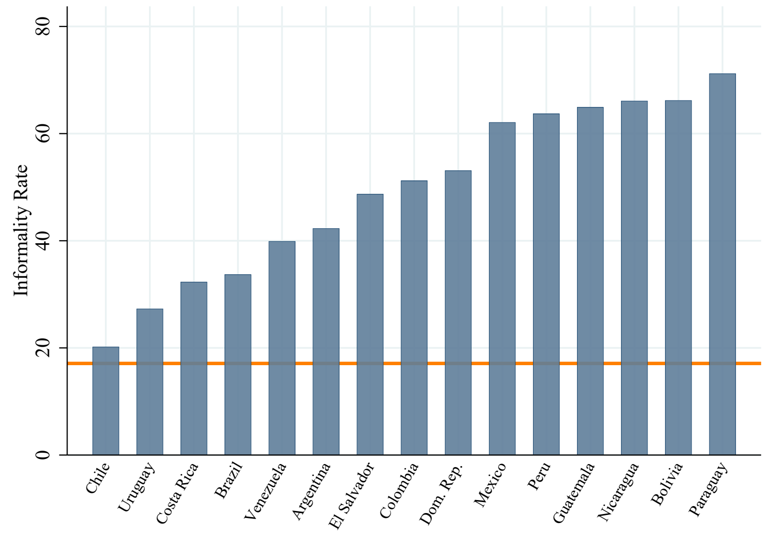
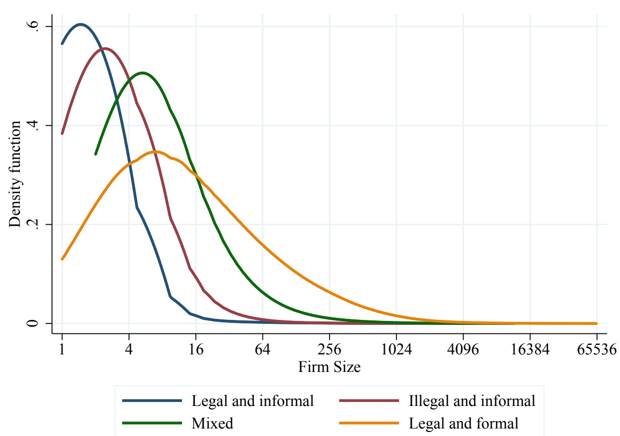
Figures

Figure 1: Informality Rates-Latin America and the Caribbean

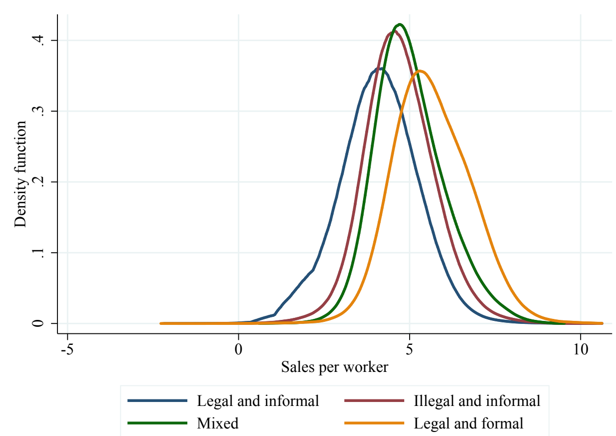


Notes: This figure plots informality rates across countries from Latin America and the Caribbean. The data source is the online appendix from Ulyssea (2018) that uses data from *SEDLAC*, an initiative from the World Bank and Universidad Nacional de la Plata. Informal workers are defined as those without 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 2: Firm size and Productivity Distribution-Economic Census 1999



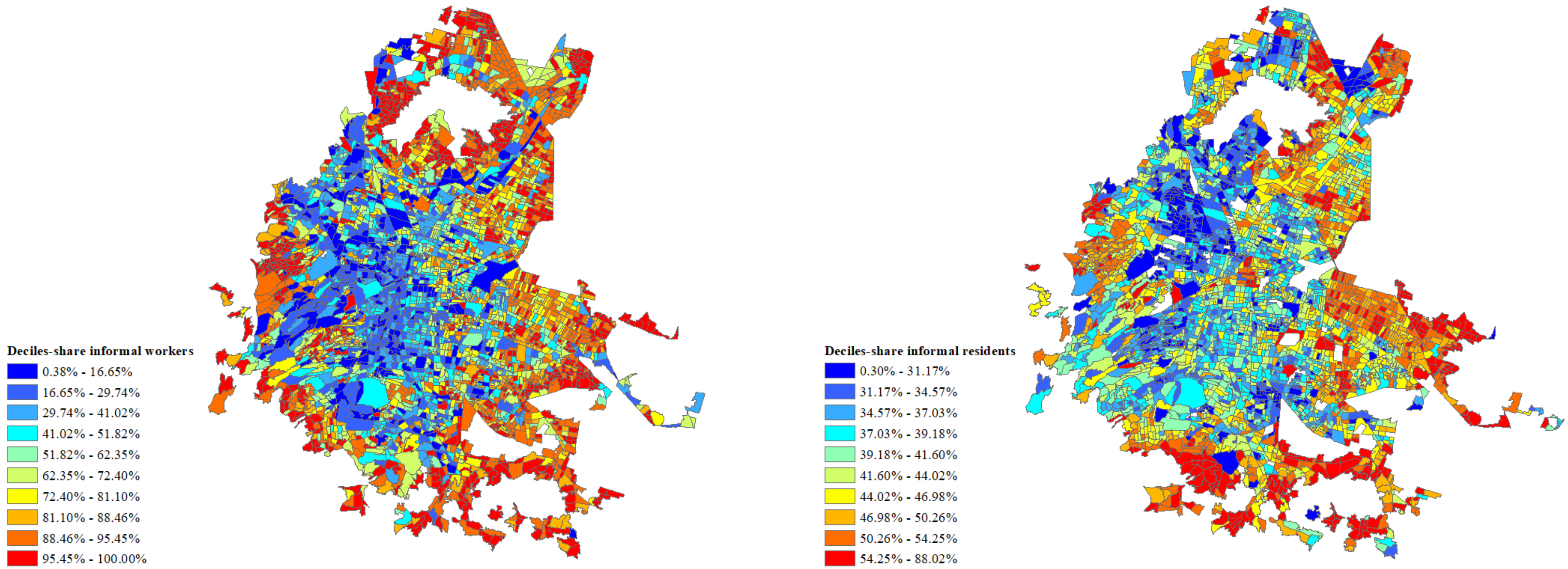
(a) Firm size



(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 3: Spatial distribution of informality

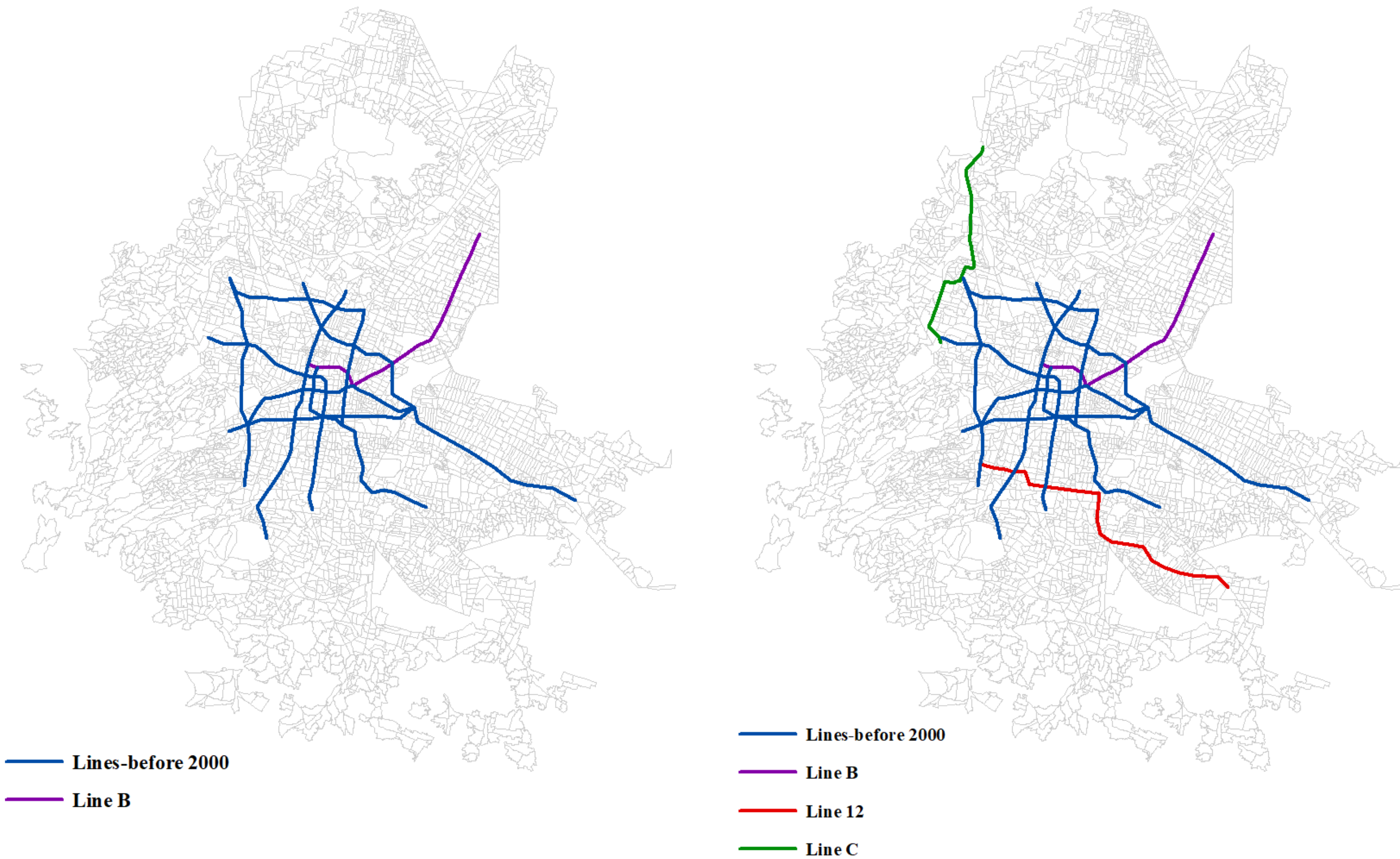


(a) Informal workers

(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 4: Transit System

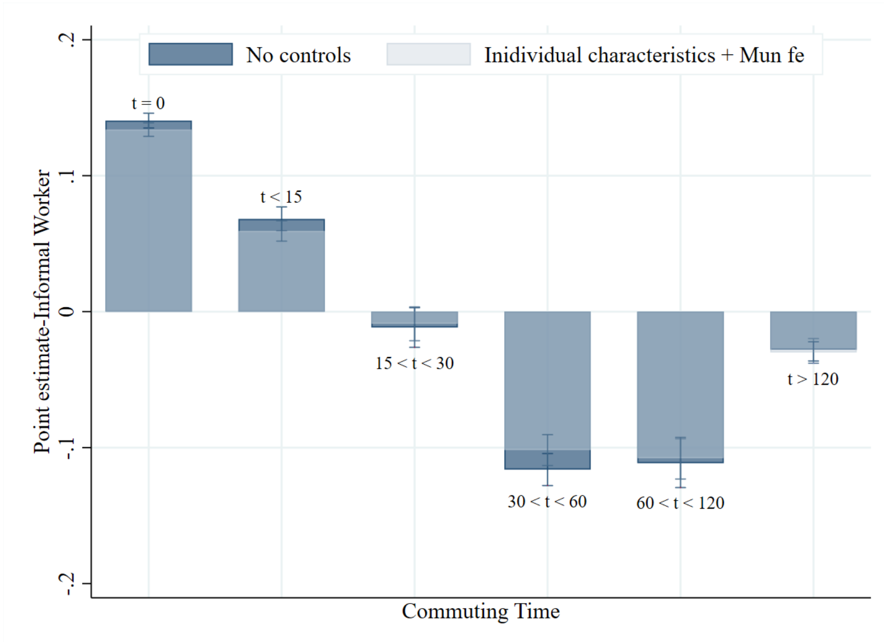


(a) Line B

(b) Other lines

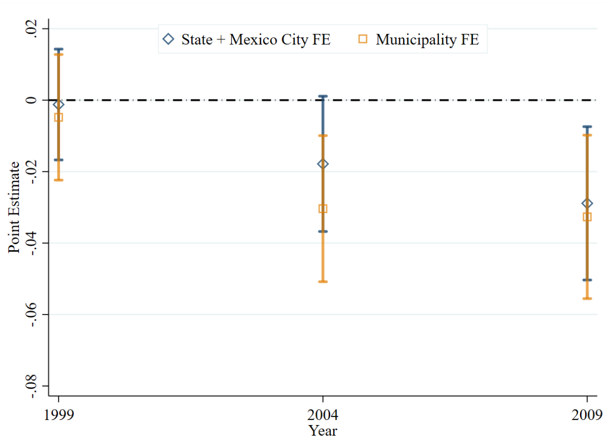
Notes: This figure plots a map of Mexico City with the transportation system. Panel (a) highlights the transit line -Line B- that I exploit in my main specification. On the other hand, panel (b) highlights the two lines that I use as a control group for the robustness checks. According to the transit 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 5: Commuting Time- Informal vs. Formal

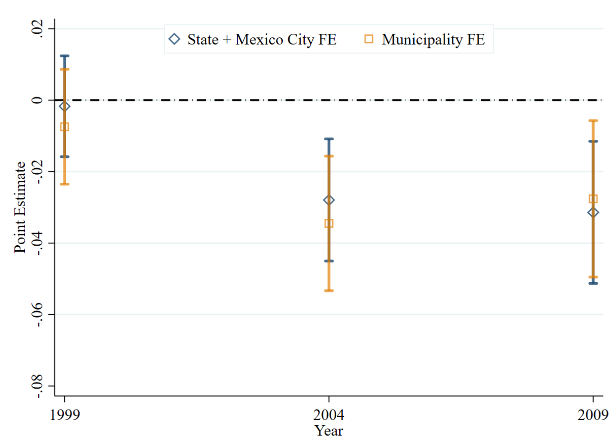


Notes: This figure plots the point estimate and 95th percentile confidence interval of a regression that relates the probability of commuting within some window of time with an informal dummy variable. The first bar reports the results for the category of non-commuting, the second bar if the worker spends 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 6: Difference in Difference Results-Workers' Informality Share



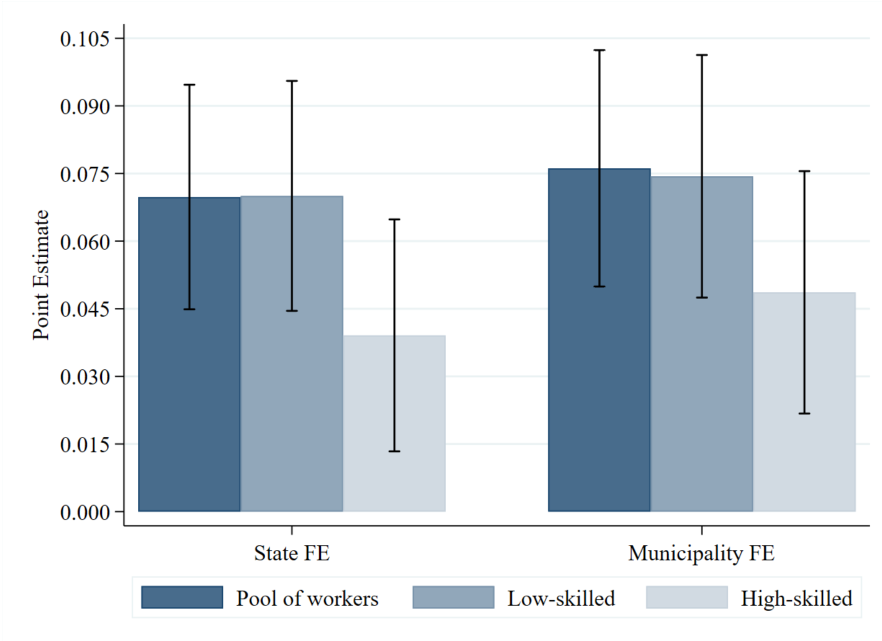
(a) Informal workers



(b) Informal and non-salaried workers

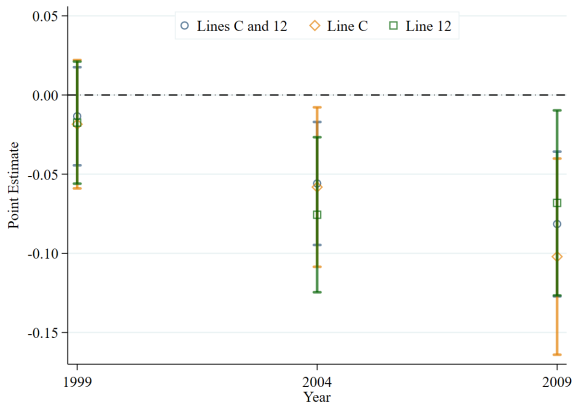
Notes: This figure depicts the point estimates and 90th percentile confidence interval from the difference in difference specification relating workers' informality rates with the transit shock. The treatment group are census tracts with centroids within a walking range of 25 minutes to stations of line 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 7: Difference in Difference Results-Residents' Informality Share

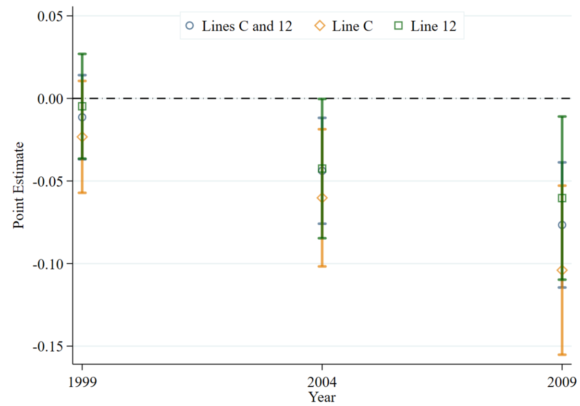


Notes: This figure depicts the point estimate and 90th percentile confidence interval of a regression that relates the change over time in the log of the ratio between formal and informal residents with the transit shock. The treatment variable takes a value of 1 for census tracts with a centroid within 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.

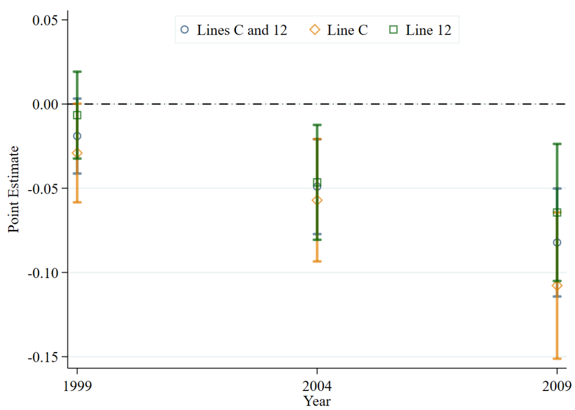
Figure 8: Robustness checks-Workers' Informality Share



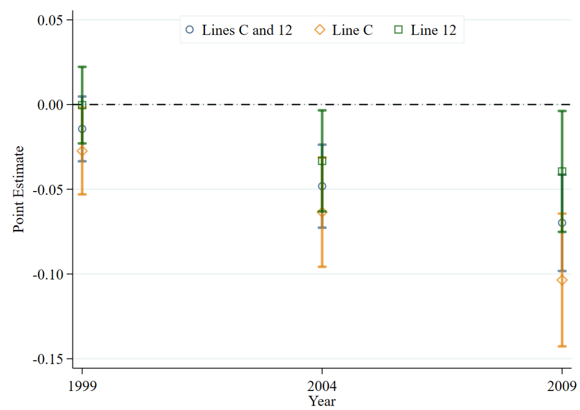
(a) Buffer: 1500 meters



(b) Buffer: 2000 meters



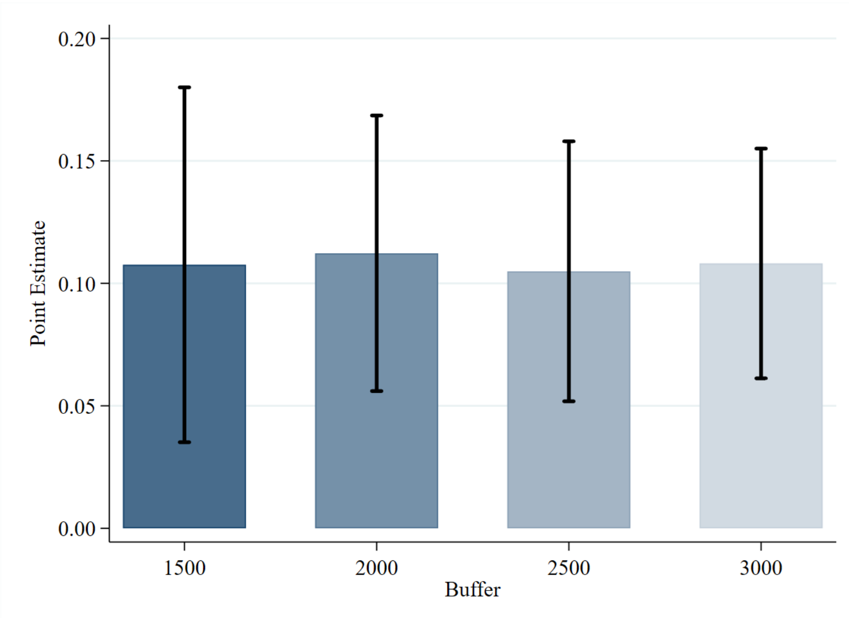
(c) Buffer: 2500 meters



(d) Buffer: 3000 meters

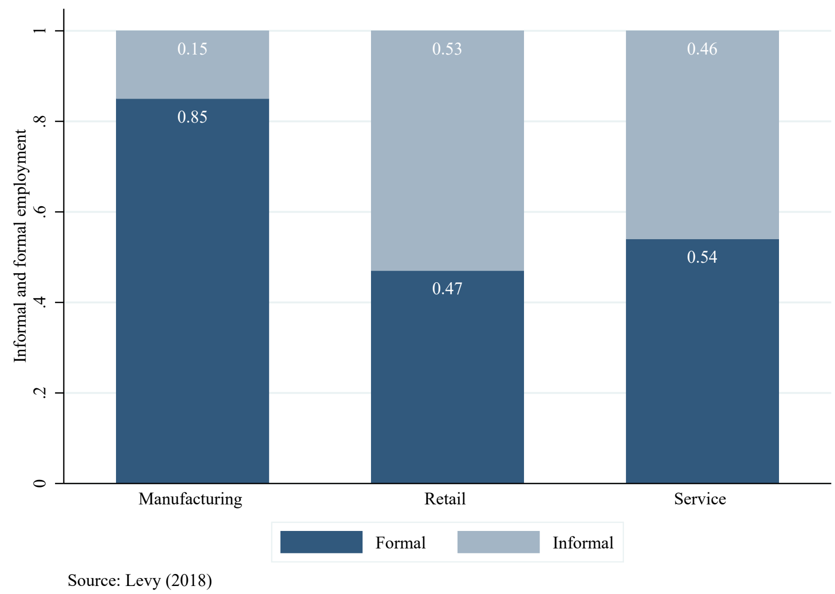
Notes: This figure depicts the point estimates and 95th percentile confidence interval from the difference-in-difference specification using different buffers and different control groups. The treatment group is defined as census tracts that are within a buffer to the new stations. The control group 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 9: Robustness Checks-Residents' Informality Share



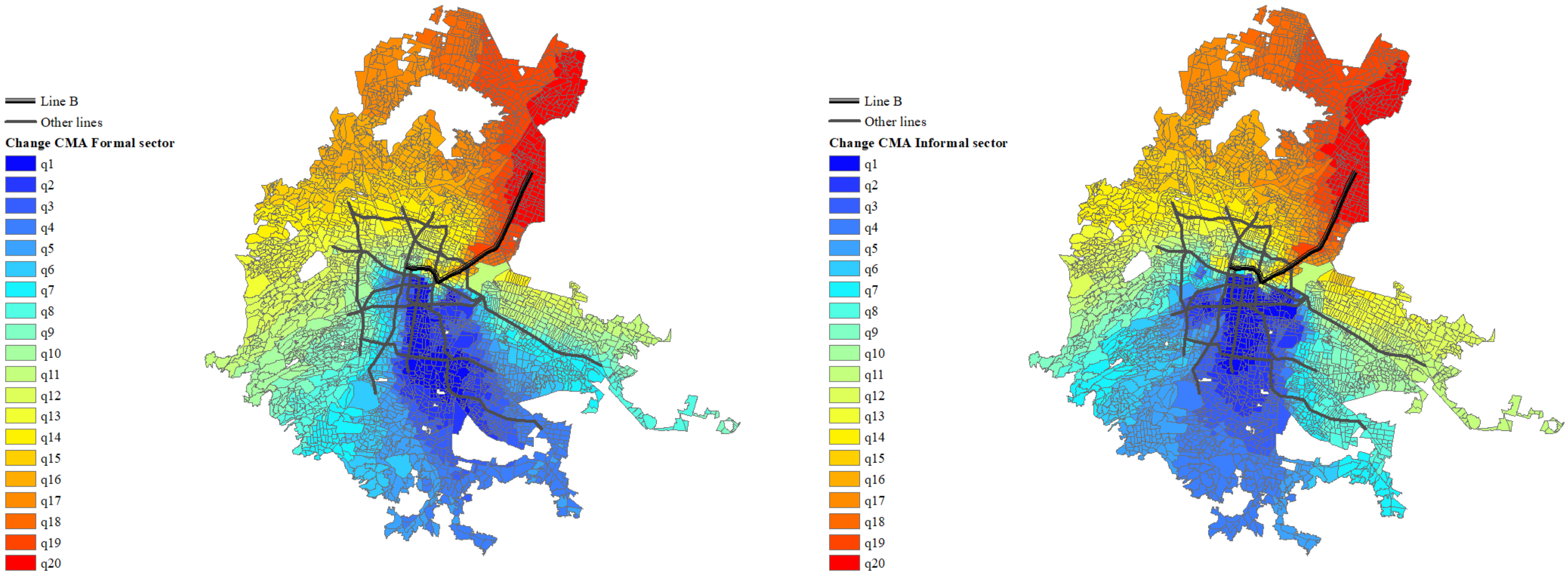
Notes: This figure depicts the point estimate and 95th percentile confidence interval of a regression that relates the change over time in the log of the ratio between formal and informal residents with the transit shock. The treatment variable takes a value of 1 for census tracts whith a centroid within 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 10: 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 11: Change in CMA for each sector

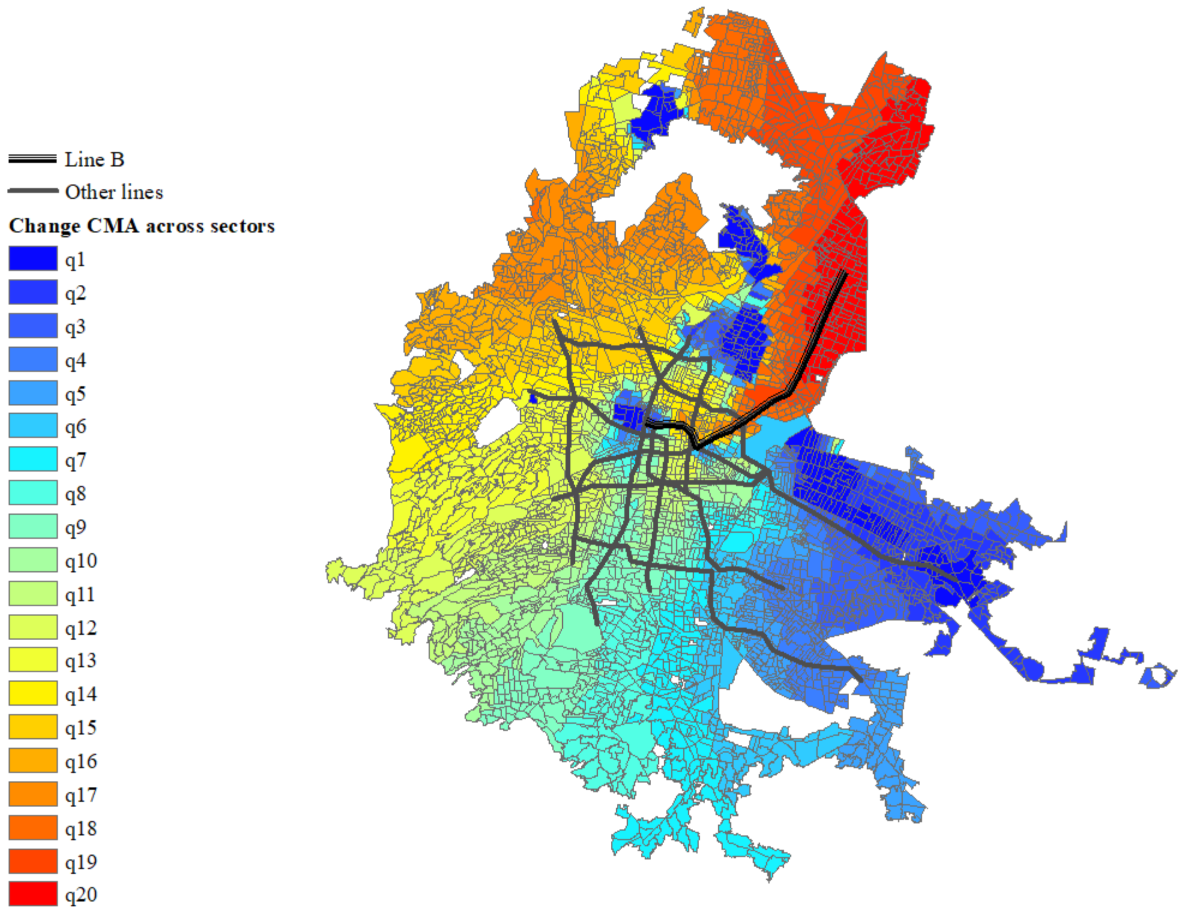


(a) Δ CMA Formal Sector

(b) Δ CMA Informal Sector

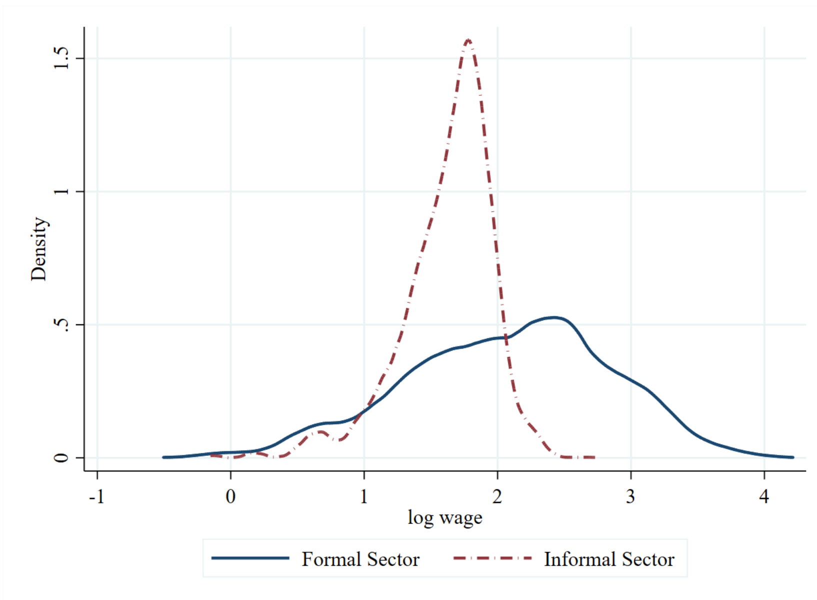
Notes: This figure plots a map of Mexico City at the census tract level with the spatial distribution of the change in CMA after the transit shock for each sector. I construct ventiles for the change in CMA across locations before and after the transit shock. Each color represents one quantile category. 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 12: Change in CMA across sectors



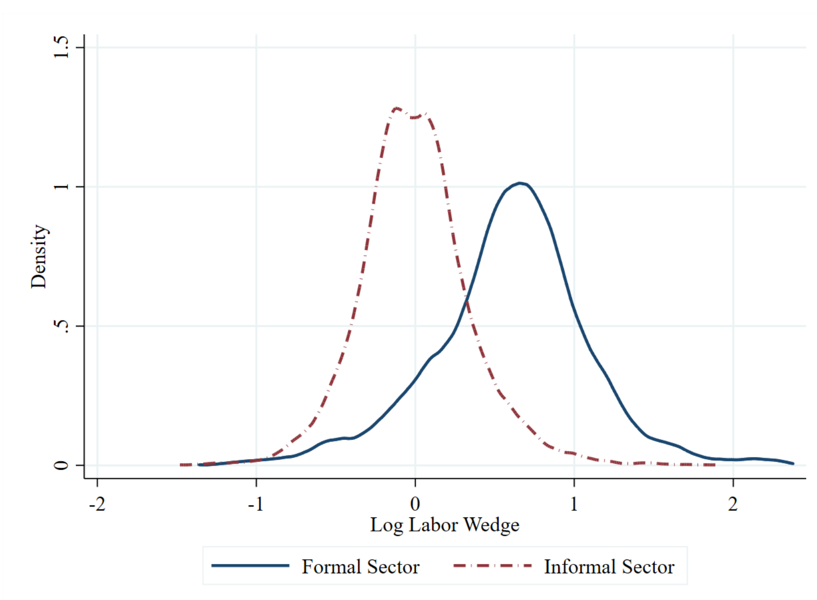
Notes: This figure plots a heat map of Mexico City with the spatial distribution of the change in CMA across sectors after the transit shock. I construct ventiles across locations by taking the difference between the formal and informal sector of CMA before and after the shock. Each color represents one of the quantile 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 13: Distribution of Wages by Sector



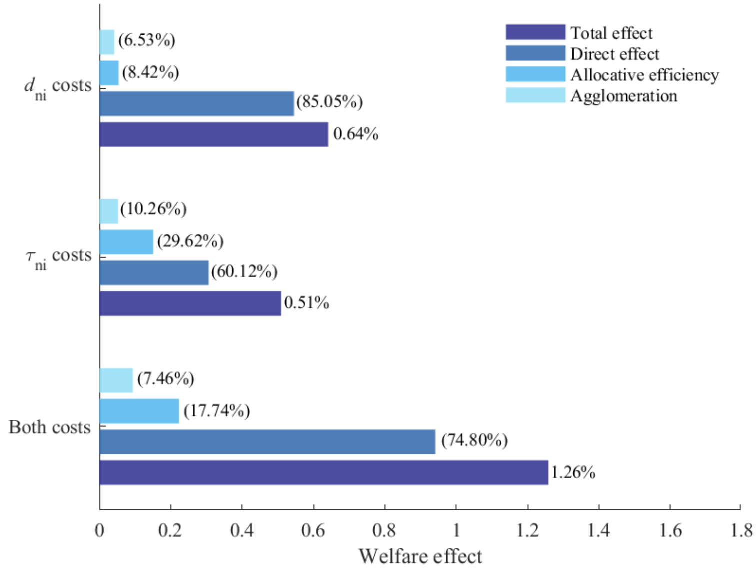
Notes: This figure plots the wage distribution obtained from the market access measures and the number of workers in each census tract. According to the definition of firm market access, $w_{is}^{\theta_s} = L_{is}\text{FMA}_{is}^{-1}$. The blue line depicts the wage distribution for the formal sector, 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 14: Distribution of Labor Wedges by Sector

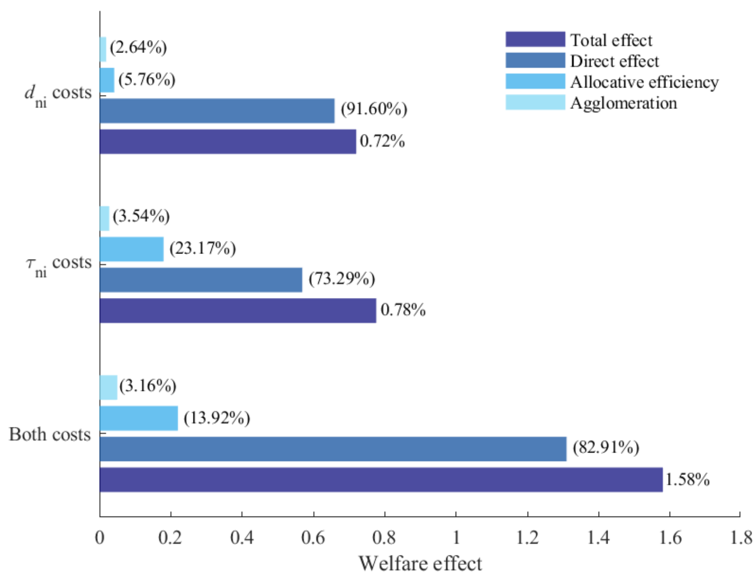


Notes: This figure plots the distribution of the labor wedge by sector across the different census tracts. I follow Hsieh and Klenow (2009) to calculate the labor wedge for each sector-location cell using the inverse of the labor share. In particular the distortion is computed using the following relations $\frac{w_{is}L_{is}}{p_{is}y_{is}}$. 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 15: Counterfactual results



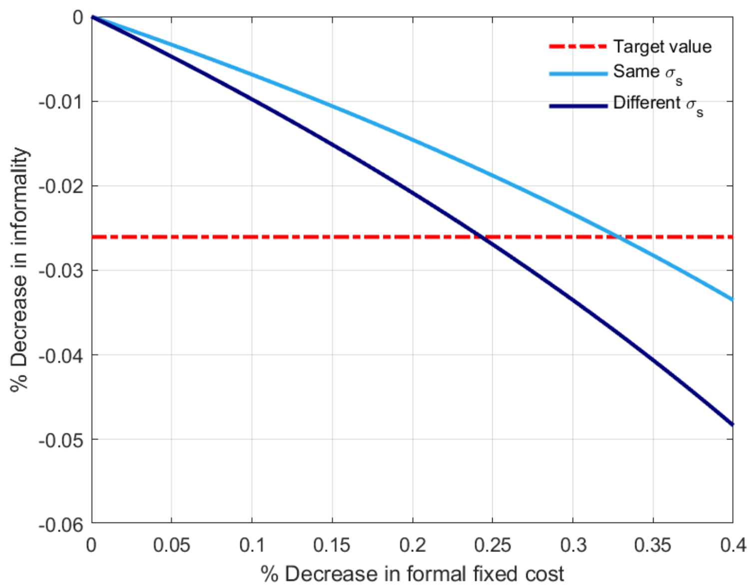
(a) No migration



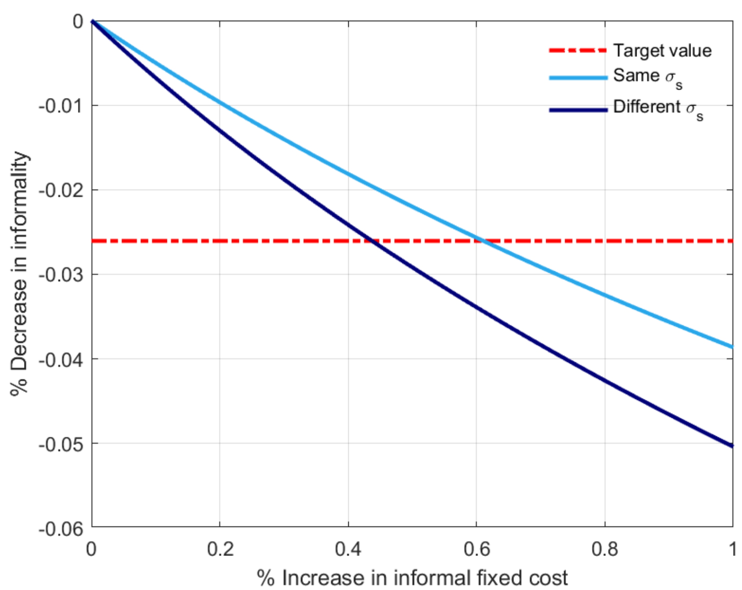
(b) Migration

Notes: This figure plots the counterfactual results. Panel (a) shows the results for the counterfactual with no migration, and panel (b) for the counterfactual in which there is migration. The blue bar represents the gains explained by the allocative efficiency margin, the red bar the gains explained by the agglomeration channel, the yellow bar represents the direct effects, and the purple bar the total gains.

Figure 16: 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 6%, which is the point estimate of the difference-in-difference specification.

Tables

Table 1: 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 2: 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	0.003	0.004	0.000	0.002	0.000	0.002	-0.002	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
-ln distance$_i$ x 1999	-0.005	-0.004	-0.010**	-0.010**	-0.014**	-0.014**	-0.016***	-0.017***
	(0.005)	(0.005)	(0.004)	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)
-ln distance$_i$ x 2004	-0.013**	-0.012**	-0.013**	-0.011**	-0.018***	-0.019***	-0.015**	-0.016**
	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.007)	(0.006)	(0.007)
Observations	12,402	12,402	12,402	12,402	12,402	12,402	12,402	12,402
R-squared	0.870	0.870	0.851	0.851	0.873	0.873	0.854	0.854
				Panel B: Treatment Measure using the dummy variable				
T_i x 1999	0.001	-0.005	-0.001	-0.008	-0.000	-0.008	-0.005	-0.015
	(0.010)	(0.009)	(0.009)	(0.008)	(0.011)	(0.010)	(0.010)	(0.009)
T_i x 2004	-0.017	-0.022*	-0.022**	-0.030***	-0.031**	-0.038***	-0.028**	-0.038***
	(0.012)	(0.012)	(0.011)	(0.010)	(0.013)	(0.012)	(0.011)	(0.011)
T_i x 2009	-0.030**	-0.032**	-0.029**	-0.032***	-0.036**	-0.038***	-0.025*	-0.030**
	(0.013)	(0.013)	(0.012)	(0.012)	(0.014)	(0.014)	(0.013)	(0.013)
Observations	12,402	12,402	12,402	12,402	12,402	12,402	12,402	12,402
R-squared	0.870	0.870	0.851	0.851	0.873	0.873	0.854	0.854
Mean outcome before the shock	0.599	0.599	0.432	0.432	0.599	0.599	0.432	0.432
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 3: 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	0.038***	0.053***	0.042***	0.057***	0.017**	0.034***	0.020**	0.038***
	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Observations	3,206	3,205	3,206	3,205	3,206	3,205	3,206	3,205
R-squared	0.161	0.246	0.161	0.247	0.225	0.296	0.225	0.297
Panel B: Treatment dummy variable-Pool of residents								
Ti	0.034**	0.070***	0.034**	0.070***	0.032*	0.076***	0.031*	0.076***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.017)	(0.016)	(0.017)	(0.016)
Observations	3,206	3,205	3,206	3,205	3,206	3,205	3,206	3,205
R-squared	0.156	0.239	0.156	0.239	0.225	0.296	0.225	0.296
Panel C: Continuous treatment measure-Low skilled residents								
- ln distance	0.044***	0.054***	0.047***	0.057***	0.017**	0.035***	0.021**	0.039***
	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)
Observations	3,207	3,205	3,207	3,205	3,207	3,205	3,207	3,205
R-squared	0.137	0.229	0.137	0.229	0.198	0.279	0.198	0.279
Panel D: Treatment dummy variable-Low skilled residents								
Ti	0.043***	0.071***	0.042**	0.070***	0.031*	0.075***	0.030*	0.074***
	(0.016)	(0.015)	(0.016)	(0.016)	(0.018)	(0.016)	(0.018)	(0.016)
Observations	3,207	3,205	3,207	3,205	3,207	3,205	3,207	3,205
R-squared	0.131	0.221	0.131	0.221	0.197	0.278	0.197	0.278
Distance	Meters	Minutes	Meters	Minutes	Meters	Minutes	Meters	Minutes
Distance+Productivity 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, and panel D for the treatment dummy variables and low skilled workers. 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 4: Change in covariates after the transit shock

	(1)	(2)	(3)	(4)
Outcome	High skill share	High skill share	Student share	Student share
T_i	-0.002	-0.003	-0.006	-0.005
	(0.003)	(0.006)	(0.004)	(0.006)
Observations	3,214	3,214	3,212	3,212
R-squared	0.164	0.236	0.316	0.332
State FE	X		X	
Municipality FE		X		X
Controls	X	X	X	X

Notes: This table reports the results of a difference-in-difference specification relating changes in household composition with the transit shock. The first two columns present the results for the share of high-skilled workers, and the second two columns for the share of students. Odd columns include state fixed effects, and even columns 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: Nested Logit - Iceberg Costs

Costs:	(1) *Commuting* Trips to Workplace	(2) *Trade* Trips to Shops
Minutes	-0.010***	-0.012***
	(0.001)	(0.001)
Bus	-0.037***	-0.058***
	(0.004)	(0.002)
Metro	-0.082***	-0.151***
	(0.004)	(0.002)
Metrobus	-0.115***	-0.212***
	(0.004)	(0.001)
Car	0.531***	-0.067***
	(0.012)	(0.002)
λ public	0.247***	0.514***
	(0.022)	(0.013)
Observations	34,640	163,280
Trips	6,928	32,656
Iceberg cost before (mean)	8.661	14.874
Iceberg cost after (mean)	7.881	13.218

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.

Table 6: Gravity equations-Commuting and Trade

	(1) Formal sector	(2) Informal sector
Panel A: commuting		
Outcome	$\ln \lambda_{niF}$	$\ln \lambda_{niI}$
Minutes	-0.033***	-0.044***
	(0.002)	(0.003)
Observations	2,304	2,304
R-squared	0.806	0.804
Implied θ	**3.33**	**4.44**
Panel B: Trade		
Outcome	$\ln \pi_{niF}$	$\ln \pi_{niI}$
Minutes	-0.037***	-0.050***
	(0.003)	(0.004)
Observations	2,304	2,304
R-squared	0.707	0.792
Implied σ	**4.08**	**5.17**
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 7: 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	0.064	-0.256***	1.068***	1.324***	1.135***	1.702***
	(0.044)	(0.059)	(0.138)	(0.188)	(0.270)	(0.414)
Observations	3,205	3,205	3,205	3,205	3,205	3,205
Adjusted R-squared	0.234	0.291	0.246	0.298	0.236	0.289
			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 First-Order			1.455***	1.180***		
			(0.092)	(0.081)		
T_i					0.061***	0.043***
					(0.005)	(0.005)
Observations			3,205	3,205	3,205	3,205
Adjusted R-squared			0.515	0.827	0.490	0.812
F-stat			250.53	213.66	133.31	90.92
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 8: Counterfactual Results $\hat{X} = X'/X$

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Percentage change in welfare					
	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	0.63%	0.52%	1.24%	0.72%	0.78%	1.58%
Decomposition						
Pure Effect	85.11%	61.78%	75.00%	92.13%	73.28%	82.78%
Allocation	8.67%	30.56%	18.82%	5.03%	23.18%	14.34%
Agglomeration	6.22%	7.66%	6.18%	2.84%	3.54%	2.88%
	Panel B: Percentage change in output					
%Δ **Output**	Δd_{ni}	$\Delta \tau_{ni}$	$\Delta d_{ni}, \Delta \tau_{ni}$	Δd_{ni}	$\Delta \tau_{ni}$	$\Delta d_{ni}, \Delta \tau_{ni}$
Total change	0.85%	0.80%	1.76%	0.57%	0.51%	1.18%
Decomposition						
Pure Effect	91.24%	73.50%	83.39%	87.60%	66.00%	77.34%
Allocation	4.66%	22.09%	12.90%	8.30%	27.99%	17.93%
Agglomeration	4.10%	4.41%	3.71%	4.11%	6.01%	4.73%

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 and panel B for output. 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.

Table 9: Total Cost of Line B

Component	Total USD millions - 2014	% of Mexico City GDP
Panel A: Infrastructure		
Investment Infrastructure	875.23	0.216%
Depreciation Cost	26.89	0.007%
Externality Cost	29.61	0.007%
Panel B: Machinery Cost		
Commercial Machinery	866.23	0.214%
Non-Commercial Machinery	617.01	0.152%
Panel C: Labor Cost		
High-Skilled	358.46	0.088%
Low Skilled	80.91	0.020%
Panel D: Operation Fixed Costs		
Labor	22.64	0.006%
Intermediate Inputs	6.59	0.002%
Machinery	5.53	0.001%
Services	1.02	0.000%
Panel E: Maintenance Fixed Costs		
Labor	9.39	0.002%
Intermediate Inputs	0.52	0.000%
Machinery	2.96	0.001%
Services	6.79	0.002%
Total	2909.78	0.717%

Notes: This table reports the costs of the project in 2014 USD prices for each of the different components. Panel A reports the total investment cost, panel B the cost of machinery, panel C the labor cost, and panel D and E the total operational and maintenance cost in the long run. This cost was calculated using a discount rate of 12% and an average inflation rate of 3%. I used an exchange rate of 13 Mexican pesos per USD in 2014.

Appendix: Spatial Misallocation, Informality, and Transit Improvements

A Additional Figures

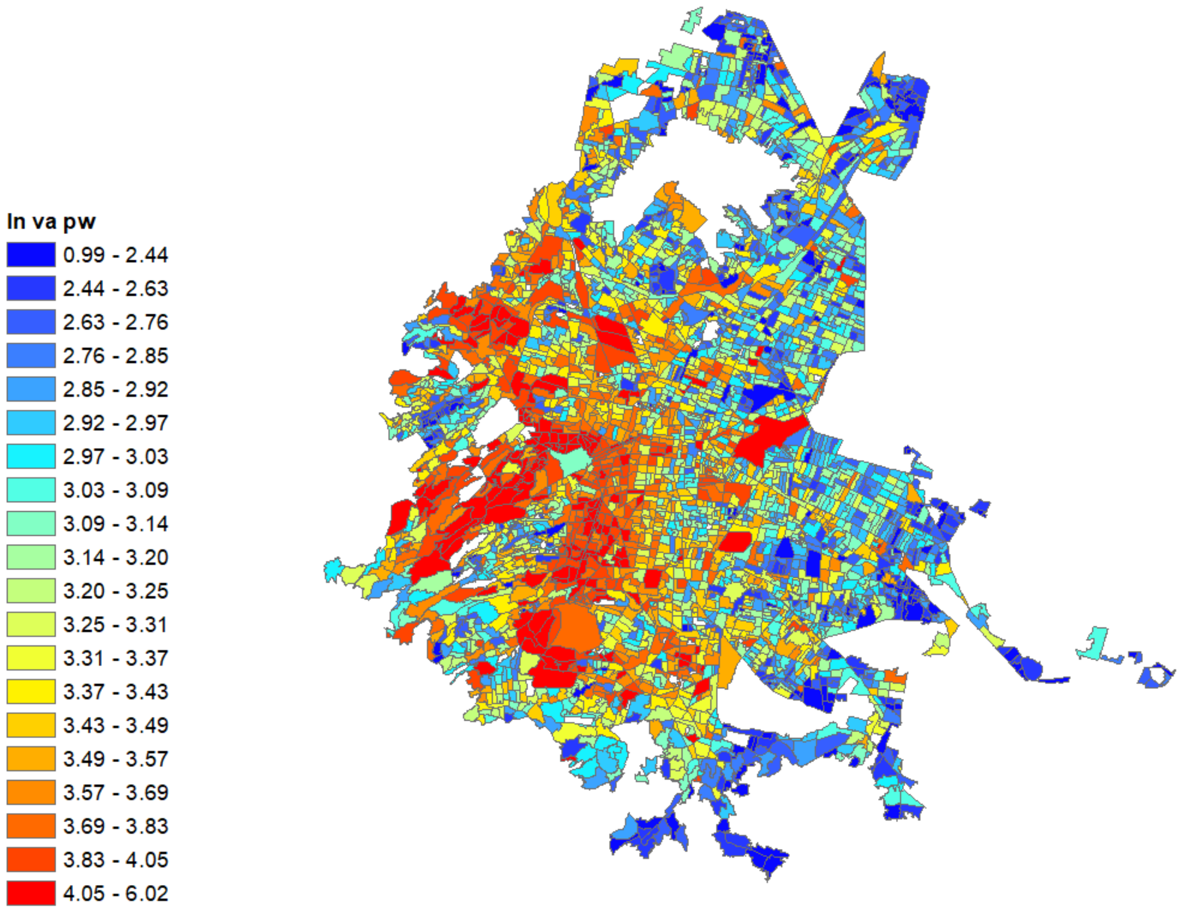
Figure A1: Locations in Mexico City

(a) Ciudad Azteca

(b) Paseo de la Reforma (Center)

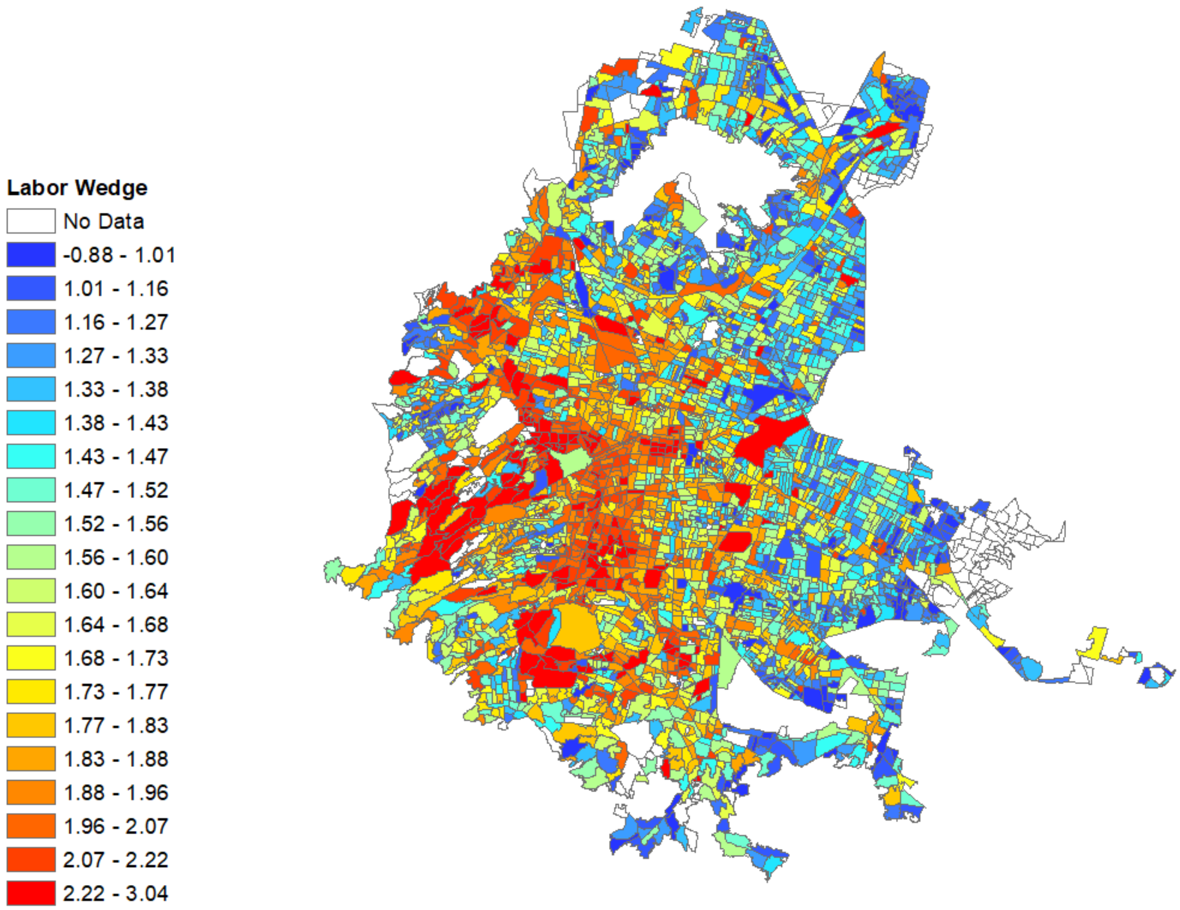
Notes: This figure plots two photos of locations in Mexico City. Panel A shows a photo of Ciudad Azteca, the last station of Line B in Ecatepec de Morelos. Panel B shows a photo of Paseo de la Reforma, a street in the central business district of the city. Line B connected census tracts around Ecatepec de Morelos with the center of the city.

Figure A2: Productivity-Spatial Distribution



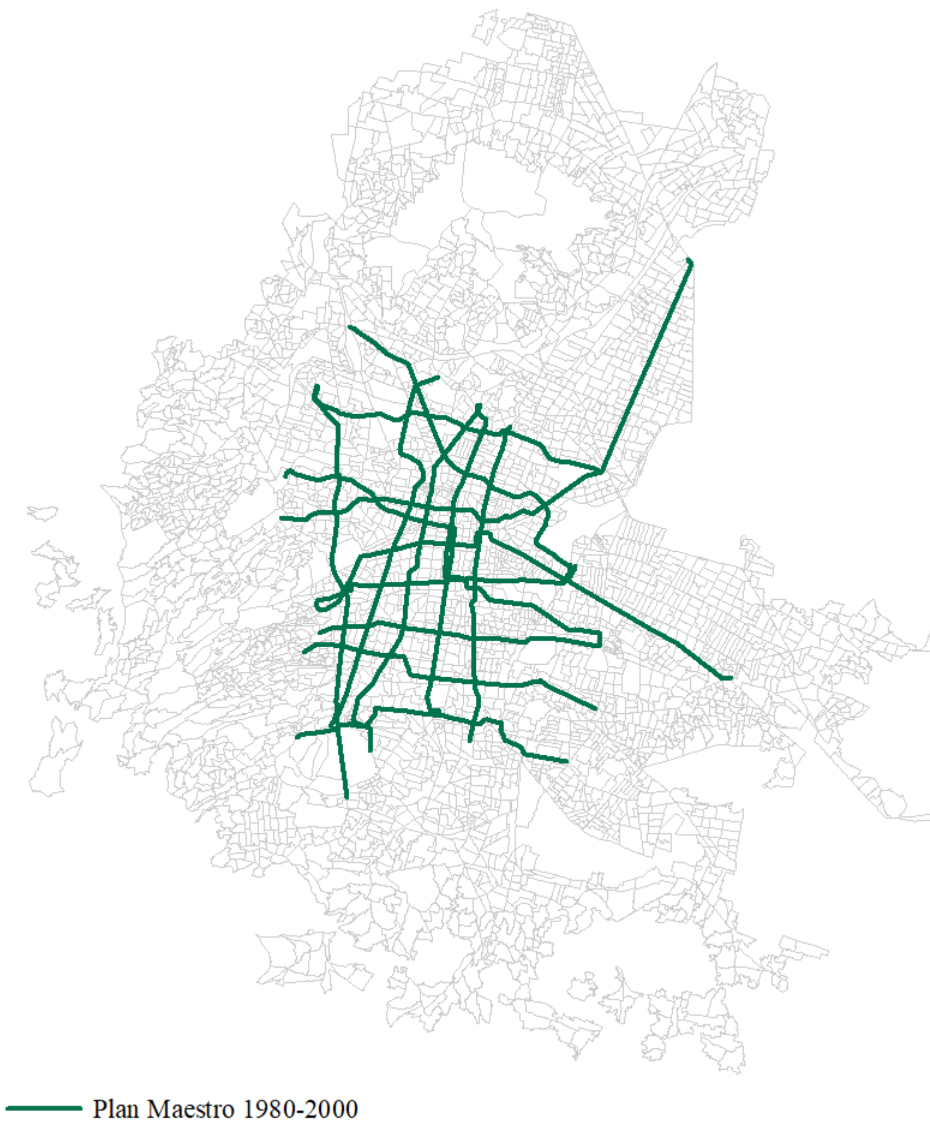
Notes: This figure plots a map of Mexico City with the spatial distribution of productivity measured as value added per worker. I construct ventiles across locations after aggregating value added measures and the total number of workers. Each color represents one of the quantile categories. Census tracts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

Figure A3: Spatial Distribution of the Labor Wedge



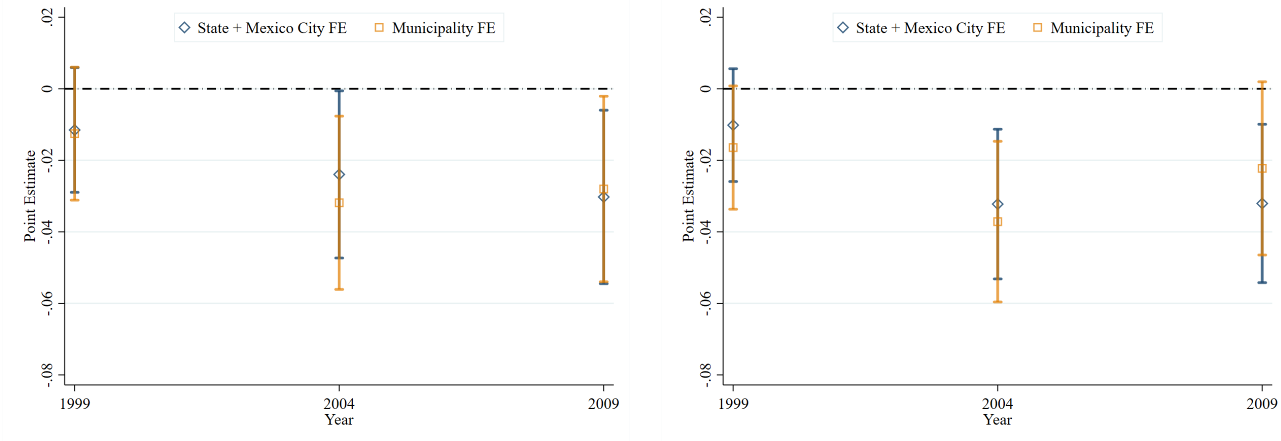
Notes: This figure plots a map of Mexico City with the spatial distribution of the average labor wedge in each location. I construct ventiles across locations after aggregating the wedge by taking the weighted average between formal and informal firms. Each color represents one of the quantile categories. Census tracts in the central areas of the city face larger wedges.

Figure A4: Plan Maestro 1985



Notes: This figure plots a map of Mexico City with the expansion plan of the Plan Maestro in 1985.

Figure A5: Difference in Difference Results-Workers' Informality Share-20 minutes

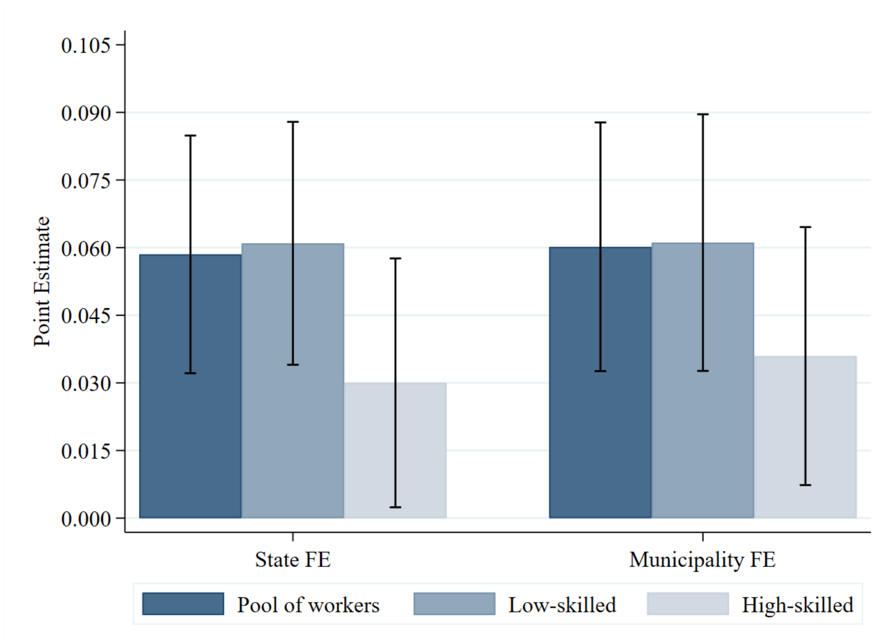


(a) Informal workers

(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 A6: 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.

B Additional Tables

Table B1: 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	46.77%	11.34%	0.00%	100.00%
Share informal high-skilled residents	35.64%	8.26%	0.00%	100.00%
Share informal low-skilled residents	50.34%	11.39%	0.01%	100.00%
Panel B: Treatment Variables				
Variable	Mean	Sd	Min	Max
Euclidean Distance to new stations (meters)	10623.33	6436.72	90.32	30903.58
Walking Distance to new stations (minutes)	119.16	70.57	1.02	382.82
Dummy variable (dist<2000)	10.00%	29.90%	0.00%	100.00%
Dummy variable (minutes<25)	10.00%	29.90%	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 B2: Results: Census tract characteristics 1999 and 2000 vs. Treatment

	(1)	(2)	(3)
Outcome:	ln Income	High Skill Share	Informality Rates
T_i	-0.038***	-0.044***	0.021***
	(0.009)	(0.008)	(0.006)
Observations	3,330	3,330	3,330
R-squared	0.249	0.196	0.093

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 B3: 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	-0.004	-0.003	-0.002	-0.005**	-0.005**	-0.005*	-0.004
	(0.004)	(0.004)	(0.003)	(0.004)	(0.002)	(0.002)	(0.003)	(0.003)
-ln distance$_i$ x 1999	-0.008	-0.006	-0.005	-0.003	-0.009***	-0.008***	-0.006**	-0.005
	(0.006)	(0.006)	(0.004)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)
-ln distance$_i$ x 2004	-0.017**	-0.016*	-0.013*	-0.013*	-0.016***	-0.017***	-0.012***	-0.013***
	(0.008)	(0.009)	(0.007)	(0.007)	(0.003)	(0.003)	(0.003)	(0.003)
Observations	12,402	12,402	12,402	12,402	12,402	12,402	12,402	12,402
R-squared	0.890	0.890	0.911	0.911	0.898	0.898	0.915	0.915
				Panel B: Treatment Measure using the dummy variable				
T_i x 1999	-0.012**	-0.012**	-0.005	-0.005	-0.009*	-0.010**	-0.007	-0.006
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
T_i x 2004	-0.020***	-0.017***	-0.014**	-0.011*	-0.017***	-0.014**	-0.014**	-0.010
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
T_i x 2009	-0.032***	-0.028***	-0.021***	-0.018***	-0.026***	-0.024***	-0.019***	-0.016**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
Observations	12,402	12,402	12,402	12,402	12,402	12,402	12,402	12,402
R-squared	0.890	0.890	0.911	0.911	0.898	0.898	0.915	0.915
Mean outcome before the shock	0.842	0.842	0.807	0.807	0.842	0.842	0.807	0.807
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 B4: Difference-in-Difference- Share of Informal Workers- Locations > 500 meters

	(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	0.001	0.002	0.001	0.002	-0.003	-0.002	-0.002	-0.001
	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.006)	(0.005)	(0.006)
-ln distance$_i$ x 1999	-0.007	-0.007	-0.011**	-0.011**	-0.015**	-0.016**	-0.018***	-0.019***
	(0.005)	(0.006)	(0.005)	(0.005)	(0.007)	(0.007)	(0.006)	(0.006)
-ln distance$_i$ x 2004	-0.015**	-0.013**	-0.015***	-0.013**	-0.018**	-0.018**	-0.016**	-0.016**
	(0.006)	(0.006)	(0.005)	(0.006)	(0.007)	(0.008)	(0.007)	(0.007)
Observation	12,292	12,292	12,292	12,292	12,292	12,292	12,292	12,292
R-squared	0.871	0.871	0.851	0.851	0.874	0.874	0.855	0.855
				Panel B: Treatment Measure using the dummy variable				
T_i x 1999	-0.006	-0.009	-0.002	-0.008	-0.007	-0.012	-0.007	-0.015
	(0.010)	(0.010)	(0.009)	(0.009)	(0.011)	(0.011)	(0.010)	(0.010)
T_i x 2004	-0.022*	-0.026**	-0.025**	-0.032***	-0.033**	-0.038***	-0.030**	-0.037***
	(0.012)	(0.012)	(0.011)	(0.011)	(0.013)	(0.013)	(0.012)	(0.012)
T_i x 2009	-0.035***	-0.034**	-0.032***	-0.035***	-0.037***	-0.037**	-0.025*	-0.028**
	(0.013)	(0.014)	(0.012)	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)
Observations	12,292	12,292	12,292	12,292	12,292	12,292	12,292	12,292
R-squared	0.871	0.871	0.851	0.851	0.874	0.874	0.855	0.855
Mean outcome before the shock	0.600	0.600	0.433	0.433	0.600	0.600	0.433	0.433
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. The sample is restricted to locations, which centroid is farther than 400 meters to the new stations using the Euclidean distance. 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 B5: Results: Number of formal workers and firms (arcsin)

	(1)	(2)	(3)	(4)
	$\ln L_{iFt}$	$\ln L_{iFt}$	$\ln M_{iFt}$	$\ln M_{iFt}$
	Panel A: Continuous Treatment Measure			
-ln distance$_i$ x 1999	0.031	0.020	0.019	0.013
	(0.029)	(0.031)	(0.017)	(0.018)
-ln distance$_i$ x 2004	-0.001	-0.007	-0.018	-0.030
	(0.038)	(0.041)	(0.021)	(0.022)
-ln distance$_i$ x 2009	0.093**	0.093**	0.047**	0.045**
	(0.041)	(0.044)	(0.020)	(0.022)
R-squared	0.894	0.894	0.910	0.910
	Panel B: Treatment using the dummy variable			
T_i x 1999	0.143*	0.052	0.072	-0.004
	(0.080)	(0.081)	(0.051)	(0.052)
T_i x 2004	0.084	0.121	0.066	0.033
	(0.117)	(0.125)	(0.065)	(0.072)
T_i x 2009	0.238**	0.264**	0.178***	0.151**
	(0.121)	(0.130)	(0.063)	(0.069)
R-squared	0.892	0.892	0.911	0.911
Observations	13,040	13,040	13,040	13,040
Distance	Meters	Minutes	Meters	Minutes
Mean number of workers/firms	653.38	653.38	21.55	21.55

Notes: This table reports the results of a regression relating changes in the log total number of formal workers and firms with the line B. The dependent variable is the arcsin of the number of formal workers and firms. Columns 1 and 2 show the results for the number of formal workers, and columns 3 and 4 for the number of formal firms. I include state fixed effects in all regressions. Standard errors are clustered at the census tract level and reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B6: Results: Number of informal workers and firms (arcsin)

	(1)	(2)	(3)	(4)
	$\ln L_{iFt}$	$\ln L_{iFt}$	$\ln M_{iFt}$	$\ln M_{iFt}$
	Panel A: Continuous Treatment Measure			
-ln distance$_i$ x 1999	-0.022	-0.022*	-0.012	-0.010
	(0.015)	(0.013)	(0.009)	(0.010)
-ln distance$_i$ x 2004	-0.076**	-0.071***	-0.024*	-0.021
	(0.037)	(0.021)	(0.013)	(0.014)
-ln distance$_i$ x 2009	-0.084*	-0.081***	-0.032**	-0.030*
	(0.043)	(0.024)	(0.016)	(0.017)
R-squared	0.908	0.908	0.913	0.913
	Panel B: Treatment using the dummy variable			
T_i x 1999	-0.050	-0.024	-0.033*	-0.023
	(0.036)	(0.035)	(0.017)	(0.016)
T_i x 2004	-0.184***	-0.176***	-0.057**	-0.057**
	(0.054)	(0.053)	(0.028)	(0.026)
T_i x 2009	-0.206***	-0.199***	-0.069**	-0.074**
	(0.053)	(0.054)	(0.029)	(0.029)
R-squared	0.908	0.908	0.913	0.913
Observations	13,040	13,040	13,040	13,040
Distance	Meters	Minutes	Meters	Minutes
Mean number of workers/firms	325.77	325.77	125.21	125.21

Notes: This table reports the results of a regression relating changes in the log total number of informal workers and firms with the line B. The dependent variable is the arcsin of the number of informal workers and firms. Columns 1 and 2 show the results for the number of informal workers, and columns 3 and 4 for the number of informal firms. I include state fixed effects in all regressions. Standard errors are clustered at the census tract level and reported in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

C Data and Quantification Appendix

C.1 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.[38] 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

[38] The data can be found here.

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, 2019). 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 C7: 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.

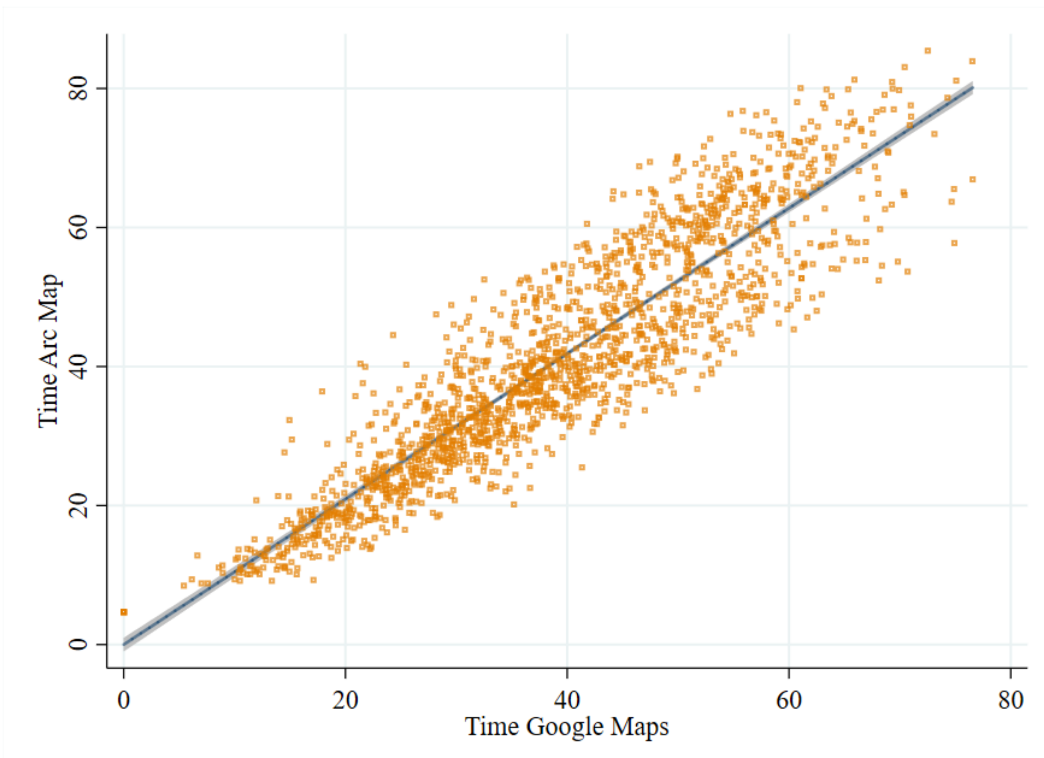
To calibrate speeds for each mode and each type of road, I use random trips from Google Maps.[39] I downloaded 4000 random trips between 8 am-11 am, and 5 pm-8 pm using the command *gmaps*

[39] 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.

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 C7 reports the average speed for each one of the roads and the public transit system.

To corroborate that the commuting times from the Network analysis toolkit are similar to the ones from Google Maps, figure C7 plots a scatter plot comparing the time across locations from Arcmap with Google maps for the transportation mode “car”. The fit of the speed calibration is good, the regression has an R-squared of 0.82, and the slope of the line is very close to 1. Differences between the two methods can arise for various reasons. For example, measurement error or the fact that Google Maps allows to calculate times for several traffic scenarios.

Figure C7: Arcmap vs. Google maps-travel time car



Notes: This figure compares travel times using Google maps vs. travel times using the network analysis toolkit from Arcmap for the car transportation mode. The R2-squared associated with this scatter plot is 0.82

C.2 Calibration of Fixed Costs

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:

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

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,

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

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 C8: 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. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table C8 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.

C.3 Labor Force Participation

In this section, I explore the relationship between labor force participation and transit improvements. I run the standard difference-in-difference equation from section 3 using the share of individuals that decide to participate in the labor market as a dependent outcome. I estimate the following equation

$$\Delta\text{Occ. share}_i = \beta \text{T}_i + \gamma X_i + \delta_{s(i)} + \epsilon_i, \tag{C.3}$$

where ΔOcc. share$_i$ is the change in the share of workers that decide to participate in the labor market, and T_i is a treatment dummy variable whether the centroid of the census-tract is within a 25 minutes walking range.

Table C9: Difference-in-difference labor market participation

	(1)	(2)	(3)	(4)
Outcome:	Δ Occ. share	Δ Occ. share	Δ Occ. share	Δ Occ. share
T_i	0.012***	0.014***	0.009***	0.012***
	(0.002)	(0.002)	(0.002)	(0.002)
Distance Controls	X	X	X	X
Population Controls		X		X
State Fe	X	X		
Municipality FE			X	X
Observations	3,323	3,321	3,323	3,321
R-squared	0.020	0.195	0.063	0.248

Notes: This table reports the results of a regression relating the change in the share of workers that participate in the labor market with the transit shock. The treatment group is defined as census-tract, which centroid is within a 25 minutes walking range, and the control group are all other census-tracts in Mexico City and adjacent municipalities. Column 1 reports the results including state fixed effect and only distance controls, column 2 adds population controls, columns 3 includes municipality fixed effects and distance controls, and column 4 adds population controls to the specification with 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 C9 reports the results. Overall, line B increased labor market participation between 1.0 and

1.4 percentage points in locations nearby to the new stations relative to other census-tracts in Mexico City. This represents an increase of approximately 2 percent using as a benchmark the average of the occupational share in 2000 (54%). The effect is robust under different specifications and sets of fixed effects. This finding implies that the line B can increase welfare even more than the results from the quantitative analysis as it increases labor market participation and total output. Even though I do not quantify this effect in the quantitative analysis, I extend the model to add labor market participation (home vs. market production) in section D.4 of the theoretical appendix.

C.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:
$$\lambda_{nisL|ns} = \frac{w_{is}^{\theta_s} d_{ni}^{-\theta_s}}{\sum_{i'} w_{i's}^{\theta_s} d_{ni'}^{-\theta_s}} \tag{C.4}$$
$$\lambda_{nsL|n} = \frac{W_{ns|n}^{\kappa}}{\sum_{s'} W_{ns'|n}^{\kappa}}, \quad W_{ns|n}^{\theta_s} = \sum_{i'} w_{is}^{\theta_s} d_{ni}^{-\theta_s} \tag{C.5}$$
$$\tilde{L}_{is} = \sum_{n} \lambda_{nis} \cdot \bar{L}_L. \tag{C.6}$$
   - Average income
$$\bar{y}_n \equiv \sum_{i,s} \lambda_{nis} w_{is} \tag{C.7}$$
   - Commercial floor space prices
$$q_i \tilde{Z}_i = \sum_{s} \frac{(1-\beta)(1+t_{isL}) w_{is} \tilde{L}_{is}}{\beta(1+t_{isZ})}, \tag{C.8}$$
   - Number of firms
$$M_{is} = \frac{\tilde{\beta} \tilde{L}_{is}^{\beta} \tilde{Z}_{is}^{1-\beta}}{\sigma_s F_s}, \tag{C.9}$$
   - Expenditure shares
$$\pi_{nis} = \underbrace{\frac{P_{ns}^{1-\xi}}{\sum_{s'} P_{ns'}^{1-\xi}}}_{\pi_{ns}} \cdot \underbrace{\frac{M_{is} p_{nis}^{1-\sigma}}{\sum_{i'} M_{i's} p_{ni's}^{1-\sigma}}}_{\pi_{nis|s}}, \quad \text{with} \quad P_{ns} = \left(\sum_{i} M_{is} p_{nis}^{1-\sigma_s} \right)^{\frac{1}{1-\sigma_s}}, \tag{C.10}$$

- Government budget constraint

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

$$\bar{t} = \frac{\alpha \cdot \delta}{1 + (1-\alpha) \cdot \delta} \tag{C.11}$$

- Aggregate Expenditure

$$X_n = \frac{(1+\bar{t})}{\alpha - \bar{t}(1-\alpha)} \left(\bar{y}_n L_n + q_n Z_n\right). \tag{C.12}$$

- Labor demand

$$Y_{is} = \alpha \sum_n \pi_{nis} X_n. \tag{C.13}$$

$$LD_{is} = \frac{\alpha \beta Y_{is}}{w_{is}^t} \tag{C.14}$$

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

$$z_w = \frac{\alpha \beta Y_{is} - w_{is}^t (1 + t_{isL}) \tilde{L}_{is}}{w_{is}^t (1 + t_{isL}) \tilde{L}_{is}} \tag{C.15}$$

$$\tilde{L}_n^t = \left(\frac{B_n P_n^{-\alpha\eta} r_n^{-(1-\alpha)\eta} W_n^{\eta}}{\sum_{n'} B_{n'} P_{n'}^{-\alpha\eta} r_{n'}^{-(1-\alpha)\eta} W_{n'}^{\eta}} \right) \bar{L}_L \tag{C.16}$$

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

$$w_{is}^{t+1} = w_{is}^t (1 + \nu_w z_w) \tag{C.17a}$$

$$L_n^{t+1} = \nu_L \tilde{L}_n^t + (1 - \nu_L) L_n^t, \tag{C.17b}$$

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

C.5 Robustness: Counterfactual results

Table C10: Robustness checks: $\hat{X} = X'/X$

	(1)	(2)	(3)	(4)	(5)	(6)
	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: Welfare, η = 1.1			
Total change	0.72%	0.64%	1.45%	0.76%	0.83%	1.67%
Decomposition						
Pure Effect	87.86%	67.48%	78.81%	92.71%	74.11%	83.58%
Allocation	7.25%	27.04%	16.59%	4.61%	22.62%	13.78%
Agglomeration	4.89%	5.48%	4.60%	2.68%	3.27%	2.64%
			Panel B: Welfare, η = 1.5			
Total change	0.63%	0.52%	1.24%	0.72%	0.78%	1.58%
Decomposition						
Pure Effect	85.11%	61.78%	75.00%	92.13%	73.28%	82.78%
Allocation	8.67%	30.56%	18.82%	5.03%	23.18%	14.34%
Agglomeration	6.22%	7.66%	6.18%	2.84%	3.54%	2.88%
			Panel C: Welfare, η = 2.0			
Total change	0.54%	0.41%	1.04%	0.66%	0.74%	1.48%
Decomposition						
Pure Effect	82.54%	53.77%	70.50%	91.97%	72.82%	82.16%
Allocation	9.72%	35.70%	21.40%	5.09%	23.78%	14.91%
Agglomeration	7.74%	10.53%	8.11%	2.95%	3.40%	2.93%
			Panel D: Welfare, η = 2.5			
Total change	0.50%	0.36%	0.94%	0.63%	0.73%	1.44%
Decomposition						
Pure Effect	81.65%	49.03%	68.29%	92.15%	72.98%	82.05%
Allocation	9.86%	38.77%	22.57%	4.88%	23.90%	15.10%
Agglomeration	8.49%	12.19%	9.14%	2.98%	3.12%	2.85%

Notes: This table reports the counterfactual results for the line B of the subway for different values of the migration elasticity η. 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 $\eta = 1.1$, panel B for $\eta = 1.5$ (baseline model), panel C for $\eta = 2.0$, and panel D for $\eta = 2.5$. 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 Theoretical Appendix

D.1 Nested Frechet Distribution

There is a mass of locations $\mathcal{N}$ indexed by n and i, and S sectors. Workers get random utility shocks from the following cumulative distribution $H(\cdot)$:

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

then, the pdf of location n, sector s and workplace i is:

$$H_{nis}(\vec{z}) = \eta U_n^{\eta-\kappa} U_{ns}^{\kappa-\theta_s} z_{nis}^{-\theta_s-1} \exp\left(-z_{nis}^{-\theta_s}\left(\sum_{n'} U_{n'}^{\eta}\right)\right) dz_{nis}, \tag{D.1}$$

where

$$U_n = B_n\left(\sum_{s'} B_{ns'}\left(\sum_{i'} z_{ni's'}^{-\theta_{s'}}\right)^{\frac{\kappa}{\theta_{s'}}}\right)^{\frac{1}{\kappa}}$$

$$U_{ns} = \left(\sum_{i'} z_{ni's'}^{-\theta_{s'}}\right)^{\frac{1}{\theta_{s'}}}$$

The probability of choosing location n sector s and workplace i is the same as the probability that $z_{n'i's'} \leq a_{n'i's'} z_{nis} = a_{n'i's'} z$ for all (n', i', s'), where

$$a_{n'i's'} = \frac{V_{nis}}{V_{n'i's'}},$$

$$V_{nis} \equiv P_n^{-\alpha} r_n^{-(1-\alpha)} w_{is} d_{ni}^{-1},$$

which is the same as the utility function in the text. Then:

$$\lambda_{nis} = \int_0^{\infty} \eta U_n^{\eta-\kappa} U_{ns}^{\kappa-\theta_s} z^{-\eta-1} \exp\left(-z^{-\eta}\left(\sum_{n'} U_{n'}^{\eta}\right)\right) dz \tag{D.2a}$$

$$= \frac{U_n^{\eta-\kappa} U_{ns}^{\kappa-\theta_s}}{\sum_{n'} U_{n'}^{\eta}} \int_0^{\infty} \eta\left(\sum_{n'} U_{n'}^{\eta}\right) z^{-\eta-1} \exp\left(-z^{-\theta_s}\left(\sum_{n'} U_{n'}^{\eta}\right)\right) dz \tag{D.2b}$$

$$= \frac{U_n^{\eta}}{\sum_{n'} U_{n'}^{\eta}} \frac{U_{ns}^{\kappa}}{U_n^{\kappa}} \frac{1}{U_{ns}^{\theta_s}}. \tag{D.2c}$$

Then, replacing $a_{n'i's'} = \frac{V_{nis}}{V_{n'i's'}}$:

$$\lambda_{nis} = \underbrace{\left(\frac{B_n P_n^{-\alpha\eta} r_n^{-(1-\alpha)\eta} W_n^{\eta}}{\sum_{n'} B_{n'} P_{n'}^{-\alpha\eta} r_{n'}^{-(1-\alpha)\eta} W_{n'}^{\eta}} \right)}_{\lambda_n} \underbrace{\left(\frac{B_{ns} W_{ns|n}^{\kappa}}{\sum_{s'} B_{ns'} W_{ns'|n}^{\kappa}} \right)}_{\lambda_{ns|n}} \underbrace{\left(\frac{w_{is}^{\theta_s} d_{ni}^{-\theta_s}}{\sum_{i'} w_{i's}^{\theta_s} d_{ni'}^{-\theta_s}} \right)}_{\lambda_{nis|ns}}. \tag{D.3}$$

Similarly, the probability that max $V_{n'i's'} z_{n'i's'} \leq x$, and that $(n, i, s) = \text{argmax}_{n'i's'}$ is equal to

$$\Pr\left(V_{n'i's'} z_{n'i's'} \leq x \;\&\; (n,i,s)\right) = \int_0^{\frac{x}{V_{nis}}} \eta U_n^{\eta-\kappa} U_{ns}^{\kappa-\theta_s} z^{-\eta-1} \exp\left(-z^{-\eta}\left(\sum_{n'} U_{n'}^{\eta}\right)\right) dz \tag{D.4a}$$

$$= \frac{U_n^{\eta}}{\sum_{n'} U_{n'}^{\eta}} \frac{U_{ns}^{\kappa}}{U_n^{\kappa}} \frac{1}{U_{ns}^{\theta_s}} \exp\left(-\left[\frac{x}{V_{nis}}\right]^{-\eta}\left(\sum_{n'} U_{n'}^{\eta}\right)\right). \tag{D.4b}$$

Defining $U^{\eta} = \sum_{n'} U_{n'}^{\eta}$, by Bayes rule:

$$\text{E}[\max V_{n'i's'} \cdot z_{n'i's'} | \text{argmax} = (n,i,s)] = \lambda_{nis}^{-1}\left(U_n^{\eta-\kappa} U_{ns}^{\kappa-\theta_s}\right) \int_0^{\infty} x^{-\eta} V_{nis}^{\eta} U^{\eta} \exp\left(-x^{-\eta} V_{nis}^{\eta} U^{\eta}\right) dx \tag{D.5a}$$

$$= V_{nis} U \gamma_{\eta} \tag{D.5b}$$

$$= V_{nis}\left(\sum_{n'}\left(\sum_{s'}\left(\sum_{i'} V_{n'i's'}^{\theta_{s'}} V_{nis}^{-\theta_{s'}}\right)^{\frac{\kappa}{\theta_{s'}}}\right)^{\frac{\eta}{\kappa}}\right)^{\frac{1}{\eta}} \gamma_{\eta} \tag{D.5c}$$

$$= \left(\sum_{n'} B_{n'} P_{n'}^{-\alpha\eta} r_n^{-(1-\alpha)\eta}\left(\sum_{s'}\left(\sum_{i'} w_{i's'}^{\theta_{s'}} d_{n'i'}^{-\theta_{s'}}\right)^{\frac{\kappa}{\theta_{s'}}}\right)^{\frac{\eta}{\kappa}}\right)^{\frac{1}{\eta}} \gamma_{\eta} \tag{D.5d}$$

$$= \left(\sum_{n'} B_{n'} P_{n'}^{-\alpha\eta} r_{n'}^{-(1-\alpha)\eta} W_{n'}^{\eta}\right)^{\frac{1}{\eta}} \gamma_{\eta}, \tag{D.5e}$$

where $\gamma_{\eta} = \Gamma\left(1 - \frac{1}{\eta}\right)$ is the constant term from the Frechet distribution. Finally, since (nis) is the argmax of $H(\cdot)$, this latter term is the same as the expected unconditional utility and we obtain the same expression as in the text.

D.2 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:

$$V_{ni\omega} = B_n \frac{d_{ni} w_{is} \epsilon_{ni\omega}}{r_n^{\beta} P_n^{1-\beta}} \tag{D.6}$$

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:

$$w_{is}d_{ni}^{-1}\tilde{L}_{nis} = \lambda_n\lambda_{ns|n}\lambda_{nis|ns}\bar{y}_n\bar{L}, \tag{D.7}$$

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:

$$\lambda_n\lambda_{ns|n}\lambda_{nis|ns}\bar{y}_n\bar{L} = \alpha\beta\sum_n \pi_{ns}\pi_{nis|s}\left(\bar{y}_n\lambda_n\bar{L} + q_n\lambda_{nZ}Z + r_n\lambda_{nH}H\right) \tag{D.8a}$$

$$q_n\lambda_{nZ} = \alpha(1-\beta)\sum_n \pi_{ns}\pi_{nis|s}\left(\bar{y}_n\lambda_n\bar{L} + q_n\lambda_{nZ}Z + r_n\lambda_{nH}H\right). \tag{D.8b}$$

And the housing market clearing condition is:

$$r_n\lambda_{nH}H = (1-\alpha)\left(\bar{y}_n\lambda_n\bar{L} + q_n\lambda_{nZ}Z + r_n\lambda_{nH}H\right) \tag{D.8c}$$

And the average utility in each location is:

$$\bar{U}_n = \frac{B_n\bar{y}_n}{P_n^{\alpha}r_n^{1-\alpha}} \tag{D.9}$$

D.2.1 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:

$$\bar{U} = \omega_L\underbrace{\sum_n \delta_n\bar{U}_n}_{\bar{U}_L} + \omega_Z\underbrace{\sum_n \delta_{nZ}\bar{U}_{nZ}}_{\bar{U}_Z} + \omega_H\underbrace{\sum_n \delta_{nH}\bar{U}_{nH}}_{\bar{U}_H}, \tag{D.10}$$

where ω and δ are weights that replicate the market allocation.[40] 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:

$$d\ln\bar{U} = \alpha\beta\sum_n \tilde{\lambda}_{nL}\left(d\ln\bar{y}_n - \alpha d\ln P_n - (1-\alpha)d\ln r_n\right) \tag{D.11a}$$

$$+ \alpha(1-\beta)\sum_n \tilde{\lambda}_{nZ}\left(d\ln q_n - \alpha d\ln P_n - (1-\alpha)d\ln r_n\right) \tag{D.11b}$$

$$+ (1-\alpha)\sum_n \tilde{\lambda}_{nH}\left(d\ln r_n - \alpha d\ln P_n - (1-\alpha)d\ln r_n\right), \tag{D.11c}$$

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

[40] To replicate the market allocation, $\bar{U} = \sum_n \bar{y}_nL_n + q_nZ_n + r_nH_n$

share of total income of commercial floor space (housing) in location n. Then, the change in the average income, and the price index is:

$$d\ln W_n = \sum_{i,s} \lambda_{ns|n}\lambda_{nis|ns} d\ln w_{is} - \sum_{i,s} \lambda_{ns|n}\lambda_{nis|ns} d\ln d_{ni} \tag{D.12a}$$

$$d\ln P_n = \sum_{i,s} \pi_{ns}\pi_{nis|s}(\beta d\ln w_{is} + (1-\beta)d\ln q_i) + \sum_{i,s} \pi_{ns}\pi_{nis|s} d\ln \tau_{ni}. \tag{D.12b}$$

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

$$d\ln \bar{U} = -\alpha\beta \sum_{n,s,i} \left(\tilde{\lambda}_{nL}\lambda_{ns|n}\lambda_{nis|ns}\right) d\ln d_{ni} \tag{D.13a}$$

$$- \alpha \sum_{n,s,i} \pi_{ns}\pi_{nis|s} \left(\alpha\beta\tilde{\lambda}_{nL} + \alpha(1-\beta)\tilde{\lambda}_{nZ} + (1-\alpha)\tilde{\lambda}_{nH}\right) d\ln \tau_{ni}. \tag{D.13b}$$

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.

D.2.2 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:

$$\lambda_n\lambda_{ns|n}\lambda_{nis|ns}\bar{y}_n\bar{L} = \frac{1+\bar{t}}{1+t_{isL}}\alpha\beta \sum_n \pi_{ns}\pi_{nis|s}\left(\bar{y}_n\lambda_n\bar{L} + q_n\lambda_{nZ}Z + r_n\lambda_{nH}H\right), \tag{D.14}$$

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:

$$d\ln \bar{U} = -\alpha\beta \sum_{n,s,i} \left(\tilde{\lambda}_{nL}\lambda_{ns|n}\lambda_{nis|ns}\right) d\ln d_{ni} \tag{D.15a}$$

$$- \alpha \sum_{n,s,i} \pi_{ns}\pi_{nis|s} \left(\alpha\beta\tilde{\lambda}_{nL} + \alpha(1-\beta)\tilde{\lambda}_{nZ} + (1-\alpha)\tilde{\lambda}_{nH}\right) d\ln \tau_{ni} \tag{D.15b}$$

$$+ \alpha\beta \sum_{n,i,s} \tilde{\lambda}_{nL}\lambda_{ns|n}\lambda_{nis|ns} \left(\frac{t_{isL}-\bar{t}}{1+\bar{t}}\right) d\ln w_{is} \tag{D.15c}$$

$$+ d\ln(1+\bar{t}). \tag{D.15d}$$

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:

$$d\ln\bar{U} = -\alpha\beta\sum_{n,s,i}\left(\tilde{\lambda}_{nL}\lambda_{ns|n}\lambda_{nis|ns}\right)d\ln d_{ni} \tag{D.16a}$$

$$-\alpha\sum_{n,s,i}\pi_{ns}\pi_{nis|s}\left(\alpha\beta\tilde{\lambda}_{nL}+\alpha(1-\beta)\tilde{\lambda}_{nZ}+(1-\alpha)\tilde{\lambda}_{nH}\right)d\ln\tau_{ni} \tag{D.16b}$$

$$+\alpha\beta\sum_{n,i,s}\tilde{\lambda}_{nL}\lambda_{ns|n}\lambda_{nis|ns}\left(\frac{t_{isL}-\bar{t}}{1+\bar{t}}\right)d\ln\tilde{L}_{nis}. \tag{D.16c}$$

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.

D.2.3 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:

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

$$d\ln\bar{U} = ... + \frac{\beta}{1+\sigma_s}\sum_{n,i,s}\left(\frac{1+t_{isL}}{1+\bar{t}}\right)d\tilde{\lambda}_{is}, \tag{D.17}$$

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,

$$d \ln \bar{U} = \underbrace{- \alpha\beta \sum_{n,i,s} \left(\tilde{\lambda}_{nL} \lambda_{ns|n} \lambda_{nis|ns} \right) \cdot d \ln d_{ni}}_{\text{“Pure” effect commuting costs}} \tag{D.18a}$$

$$\underbrace{- \alpha \sum_{n,i,s} \pi_{ns} \pi_{nis|s} \left(\alpha\beta\tilde{\lambda}_{nL} + \alpha(1-\beta)\tilde{\lambda}_{nZ} + (1-\alpha)\tilde{\lambda}_{nH} \right) d \ln \tau_{ni}}_{\text{“Pure” effect trade costs}} \tag{D.18b}$$

$$\underbrace{+ \alpha\beta \left(\sum_{n,i,s} \tilde{\lambda}_{nL} \lambda_{ns|n} \lambda_{nis|ns} \left(\frac{t_{isL} - \bar{t}}{1 + \bar{t}} \right) d \ln \tilde{L}_{nis} \right)}_{\text{Allocative efficiency}} \tag{D.18c}$$

$$\underbrace{+ \sum_{n,i,s} \frac{1}{\sigma_s - 1} \sum_{g} \beta_g \left(\frac{1 + t_{isg}}{1 + \bar{t}} \right) d\tilde{\lambda}_{isg},}_{\text{Agglomeration Forces}} \tag{D.18d}$$

which is the same expression as in the text.

D.3 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.[41] 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

[41] 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 $E_{ns}^{\frac{\theta_s}{\theta_s-1}} = \sum_i E_{nis}^{\frac{\theta_s}{\theta_s-1}}$.

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:

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

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

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

$$L_{ng}\left(P_n^* c_{ng} + r_n^* h_{ng}\right) = L_{ng}\omega_{ng} U_{ng} \tag{D.19}$$

The LHS of equation D.19 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 D.19, 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:

$$[Q_{nis}] : P_n^* \frac{\partial C}{\partial Q_{nis}} \leq p_{is}^* \tau_{ni} \tag{D.20a}$$

$$[\tilde{E}_{isg}] : p_{is}^* \frac{\partial Y}{\partial \tilde{E}_{isg}} \leq w_{isg}^* \tag{D.20b}$$

$$[E_{nisg}] : w_{isg}^* d_{ni}^{-1} \leq \bar{y}_{ng} \frac{\partial E_g}{\partial E_{nisg}} \tag{D.20c}$$

$$[\tilde{E}_{nhg}] : r_n^* \frac{\partial H}{\partial \tilde{E}_{nhg}} \leq w_{nhg} \tag{D.20d}$$

$$[L_{ng}] : \bar{y}_n \leq \Psi_g \tag{D.20e}$$

Equations D.20a to D.20d 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:

$$d\ln\bar{U} = \underbrace{-\sum_{n,i,s,g}\alpha_{ng}\beta_{isg}\left(\tilde{\lambda}_{ng}\lambda_{nsg|n}\lambda_{nisg|ns}\right)\cdot d\ln d_{ni}}_{\text{"Pure" effect commuting costs}} \tag{D.21a}$$

$$\underbrace{-\sum_{n,i,s,g}\pi_{ns}\pi_{nis|s}\left(\alpha_{ng}\beta_{isg}\tilde{\lambda}_{ng}\right)d\ln\tau_{ni}}_{\text{"Pure" effect trade costs}} \tag{D.21b}$$

$$+\underbrace{\left(\sum_{n,i,s,g}\alpha_{ng}\beta_{isg}\tilde{\lambda}_{ng}\lambda_{nsg|n}\lambda_{nisg|ns}\left(\frac{t_{isg}-\bar{t}}{1+\bar{t}}\right)d\ln\tilde{L}_{nisg}\right)}_{\text{Allocative efficiency}} \tag{D.21c}$$

$$+\underbrace{\sum_{n,i,s,g}\frac{\beta_g}{\sigma_s-1}\left(\frac{1+t_{isg}}{1+\bar{t}}\right)d\tilde{\lambda}_{isg}}_{\text{Agglomeration Forces}}. \tag{D.21d}$$

This result is similar to the one obtained by Baqaee and Farhi (2019) 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.

D.4 Labor Market Participation

In this section, I consider an extension of the model adding home production given the results from subsection C.3. In particular, workers draw productivity draws from a Nested Frechét distribution with an additional nest with respect to the model in the text: home or market production. Workers now make four decisions: 1) where to live, 2) whether to home or market produce, 3) the sector to work; and finally 4) the workplace. Random productivity shocks are drawn from the following distribution:

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

where h indexes home or market produce, D_{nh} is a productivity term for home and market production in location n, and ϵ is the dispersion parameter of this additional nest. Both, the formal and informal sector only operate in the market production economy. Then, there are no additional nests after a worker chooses to home produce. The other parameters represent the same variables as in section 4. Similarly, preferences are drawn from a Nested CES. The price index in each location is given by:

$$P_n^{1-\chi} = \sum_h P_{nh}^{1-\chi},$$

$$P_{nH} = w_{nH}$$

$$P_{nM}^{1-\xi} = \sum_{s\in\{I,F\}} P_{ns}^{1-\xi}$$

where the parameter χ captures the substitutability between home and market production, the price index P_{nH} captures the price from Home production in location n, which only uses as a factor of production, labor. Additionally, only workers that live in location n consume the Home production good of this location, and the price indices P_{ns} are the same as in equation 4.5. All the equilibrium conditions are very similar to the text, but now we have an additional goods market clearing condition from the Home Production economy.[42]. Thus, I only provide for the new goods market clearing conditions to close the model. The new equilibrium conditions are described by the following $N \times S + 1$ system of equations:

$$w_{is}(1 + t_{isL})\tilde{L}_{is} = \alpha\beta \sum_{n} \pi_{nis} X_n \tag{D.22a}$$

$$w_{nH}\tilde{L}_{nH} = \alpha\pi_{nH} X_n, \tag{D.22b}$$

where $\pi_{nis} = (1 - \pi_{nH})\pi_{ns}\pi_{nis|s}$ is the expenditure share in location n spent on the Market production good, sector s from location i, and $\pi_{nH} \equiv \frac{P_{nh}^{1-\chi}}{P_{n}^{1-\chi}}$ is the expenditure share in location n spent in the home production good. Using data on the average income from the population census and the number of people that do not participate in the labor market, I can invert the model to recover the parameters D_{nh}, and then compute the counterfactuals in this extension.[43]

Finally, I would be able to estimate the parameter ϵ by running a similar equation to 5.5. In particular, I can estimate the following equation relating changes in labor force participation to the transit shock as in section C.3:

$$\Delta \ln L_{Mi} - \Delta \ln L_{Hi} = \epsilon \left(\Delta \ln W_{Mi} - \Delta \ln w_{Hi}\right) + \gamma X_i + \delta_{s(i)} + e_i,$$

where Δ represents change over time before and after the transit shock, W_{Mi} is a wage index of the market production sector that can be constructed using measures of market access, and w_{Hi} is the wage in the Home production sector in location i that can be recovered using changes in the average income of workers that do not participate in the labor market. The parameter X_i is a vector of census tract characteristics, and $\delta_{s(i)}$ are state or municipality fixed effects.

D.5 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:

[42] These equations include the housing and commercial floor space market clearing conditions, and the average welfare in the economy

[43] Note that in this case equilibrium conditions of the efficient allocation are the same as in the previous section since the only assumption is that the efficient units aggregator $E(\cdot)$ is homogeneous of degree one. The Nested Fréchet distribution has this property.

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

then, the change in the average utility is

$$\hat{U} = \left(\sum_n \lambda_n \hat{P}_n^{-\alpha\eta} \hat{r}_n^{-(1-\alpha)\eta} \hat{W}_n^{\eta} \right)^{\frac{1}{\eta}}, \tag{D.23}$$

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:

$$\hat{P}_{ns} = \left(\sum_i \pi_{ni|s} \hat{p}_{is}^{1-\sigma_s} \right)^{\frac{1}{1-\sigma_s}} \tag{D.24a}$$

$$\hat{P}_n = \left(\sum_i \pi_{ns} \cdot \hat{P}_{ns}^{1-\xi} \right)^{\frac{1}{1-\xi}} \tag{D.24b}$$

$$\hat{W}_{ns} = \left(\sum_i \lambda_{nis|ns} \cdot \hat{w}_{is}^{\theta_s} \hat{d}_{ni}^{-\theta_s} \right)^{\frac{1}{\theta_s}} \tag{D.24c}$$

$$\hat{W}_n = \left(\sum_s \lambda_{ns|n} \cdot \hat{W}_{ns}^{\kappa} \right)^{\frac{1}{\kappa}}. \tag{D.24d}$$

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

$$\hat{\lambda}_n = \frac{\hat{P}_n^{-\eta} \hat{W}_n^{\eta}}{\sum_{n'} \lambda_{n'} \cdot \hat{P}_{n'}^{-\eta} \hat{W}_{n'}^{\eta}} = \frac{\hat{P}_n^{-\eta} \hat{W}_n^{\eta}}{\hat{U}^{\eta}} \tag{D.25a}$$

$$\hat{\lambda}_{ns|n} = \frac{\hat{W}_{ns}^{\kappa}}{\sum_k \lambda_{nk|n} \cdot \hat{W}_{nk}^{\kappa}} = \frac{\hat{W}_{ns}^{\kappa}}{\hat{W}_n} \tag{D.25b}$$

$$\hat{\lambda}_{nis|ns} = \frac{\hat{w}_{is}^{\theta_s} \hat{d}_{ni}^{-\theta_s}}{\sum_l \lambda_{nls|ns} \cdot \hat{w}_l^{\theta_s} \hat{d}_{nl}^{\theta_s}} = \frac{\hat{w}_{is}^{\theta_s} \hat{d}_{ni}^{-\theta_s}}{\hat{W}_{ns}^{\theta_s}}. \tag{D.25c}$$

And the change in the expenditure shares is:

$$\hat{\pi}_{ns} = \frac{\hat{P}_{ns}^{1-\xi}}{\sum_k \pi_{nk} \hat{P}_{nk}^{1-\xi}} = \frac{\hat{P}_{ns}^{1-\xi}}{\hat{P}_n^{1-\xi}} \tag{D.26a}$$

$$\hat{\pi}_{ni|s} = \frac{\hat{p}_{nis}^{1-\sigma_s}}{\sum_l \pi_{nls|s} \hat{p}_{nls}^{1-\sigma_s}} = \frac{\hat{p}_{nis}^{1-\sigma_s}}{\hat{P}_{ns}^{1-\sigma_s}}. \tag{D.26b}$$

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

$$\hat{\bar{y}}_n = \sum_{i,s} \lambda^Y_{nis} \hat{\lambda}_{nis|ns} \hat{\lambda}_{ns|n} \hat{w}_{is}, \tag{D.27}$$

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

$$\hat{X}_n = \widehat{(1+\bar{t})} \left(\omega_{nL} \hat{\bar{y}}_n \hat{\lambda}_n + \omega_{nZ} \hat{q}_n + \omega_{nH} \hat{r}_n \right), \tag{D.28}$$

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:

$$\hat{w}_{is} \sum_n \tilde{\lambda}_{ni} \hat{\lambda}_{nis|ns} \hat{\lambda}_{ns|n} \hat{\lambda}_n = \sum_n \pi^X_{nis} \hat{\pi}_{ns} \hat{\pi}_{nis|s} \hat{X}_n, \tag{D.29}$$

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 D.29.

D.6 Welfare Decomposition - Exact Hat Algebra

This section provides a formula to decompose the welfare effects of trade/commuting shocks into a direct effect and an allocative efficiency term using exact hat algebra. I assume for simplicity that $\alpha = 1$, $\beta = 1$. Following Holmes et al. (2014) and Asturias et al. (2016), welfare in location n can be decomposed into the following terms:

$$U_n = \underbrace{\left[\frac{\bar{y}^{ND}_n}{P^{ND}_n} \right]}_{\text{Efficiency term}} \times \underbrace{\left[\frac{(1+\bar{t}) \cdot MD_n}{MU_n} \right]}_{\text{ToT/ToC term}} \times \underbrace{\left[\frac{P^{ND}_n \cdot MU_n}{P_n} \times \frac{\bar{y}_n}{\bar{y}^{ND}_n \cdot MD_n} \right]}_{\text{Allocation/Agglomeration}}$$

where the first term corresponds to the average real income of location n in the absence of labor wedges or in the perfectly efficient case, the second term captures a terms of trade/commuting effect that represents differences on how the labor wedge affect prices (wages) of trade (commuting) outflows relative to inflows. And the last term captures the allocative efficiency and agglomeration mechanism. Finally, the variables MU_n and MD_n represent how does the presence of wedges affect prices and wages. In particular,

$$\frac{1}{MU_n} \equiv \sum_s \pi_{ns} \sum_l \pi_{nls} \cdot (1+\tau_{lsL})^{\frac{-\theta_s}{\sigma_{Ls}+\theta_s}}$$
$$MD_n \equiv \sum_s \lambda_{ns} \sum_l \lambda_{nls|ns} \cdot (1+\tau_{lsL})^{\frac{-\sigma_{Ls}}{\sigma_{Ls}+\theta_s}}.$$

where σ_{Ls} is the demand elasticity with respect to labor $\frac{d \ln PY}{d \ln L} = -\beta(\sigma_s - 1)$ to capture responses of the labor demand. This equation comes from the incidence principle of taxation. The first variable $\frac{1}{MU_n}$ is the effect of labor wedges on prices. The exponent $\frac{-\theta_s}{\sigma_{Ls}+\theta_s}$ captures the pass-through rate of labor taxes to prices. It depends on two terms, the labor demand elasticity σ_L, and the labor supply elasticity θ_s. When the labor supply elasticity θ_s is infinity, all changes in taxes are pass-through to prices. When the labor demand elasticity $\sigma_L \rightarrow \infty$ all changes in taxes are pass through to wages. On the other hand, the second term represents the effect of labor wedges on wages, and the exponent captures the pass through rate of wedges to labor payments. Then, using exact hat algebra, the total change in welfare is:

$$\hat{U} = \left(\sum_n \lambda_n \hat{U}_n^{\eta} \right)^{\frac{1}{\eta}}, \tag{D.30}$$

or taking changes in logs:

$$\Delta \ln U = \sum_n \lambda_n \left(\underbrace{\Delta \ln \bar{y}_n^{ND} - \Delta \ln P_n^{ND}}_{\text{Direct Effect}} + \underbrace{\Delta \ln \left[\frac{(1+\bar{t}) \cdot MD_n}{MU_n} \right]}_{\text{ToT/ToC}} + \underbrace{\Delta \ln \left[\frac{P_n^{ND} \cdot MU_n}{P_n} \times \frac{\bar{y}_n}{\bar{y}_n^{ND} \cdot MD_n} \right]}_{\text{Allocative Efficiency}} \right) \tag{D.31}$$

D.7 Over-identification Test

Relationship between the wage bill and firm market access measures

In this section, I show an over-identification test using firm market access measures and sales in each census tract-sector cell to estimate the commuting elasticity for both sectors. In particular, I can test for a log-linear relationship between the aggregate wage bill paid by firms, and firm market access measures at the sector level. I can recover the commuting elasticity for both sectors using a guess for β. Thus, the model is over-indentified. The total amount of income $\tilde{I}$ received by workers employed by location i and sector s is:

$$\tilde{I}_{is} = w_{is}^{-1} \alpha \beta \sum_n \pi_{ns} \pi_{nis|s} X_n,$$

where X_n is total expenditure from location n. After some algebra manipulation we arrive to the following log linear relationship relating the total wagebill vs. FMA:[44]

$$\ln \tilde{I}_{iF,t} - \ln \tilde{I}_{iF,t} = \alpha_0 + \beta \left(\alpha_F \ln \text{FMA}_{iF,t} - \alpha_I \ln \text{FMA}_{iI,t} \right) + \gamma_i + \gamma_t + \ln \epsilon_{i,t}, \tag{D.32}$$

where $\alpha_s = \frac{1}{\theta_s(1-\beta)+\beta}$, γ_{is} is a location-sector fixed effect, and γ_t is a time fixed effect.

[44] The term $\ln \epsilon_i = \Delta_s \frac{(1-\beta)\theta}{(1-\beta)\theta+1} \ln \tilde{S}_{is} + \frac{(\sigma-1)\theta}{\sigma((1-\beta)\theta+1)} \ln T_{is} + \frac{\theta}{\sigma((1-\beta)\theta+1)} \ln Y_{is}$, where $Y_{is} = \sum_n \pi_{ns} P_{ns}^{-(1-\sigma)} X_n$. In the case of a freely tradable good this last term is absorbed by the time fixed effect.