Better or worse job accessibility? Understanding changes in spatial mismatch at the intra-urban level: evidence from Medellín, Colombia*

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Abstract

We propose a methodology to calculate spatial mismatch, which incorporates both monetary transportation costs and opportunity costs while correcting for possible overestimation of job accessibility. This methodology also enables the analysis of spatiotemporal changes in spatial mismatch without discarding data from spatial units that change over time. We apply the methodology to measure spatial mismatch and its evolution in Medellín, Colombia, –a developing country city– for public and private transportation from 2012 to 2017. The results indicate that including transportation and opportunity costs leads to a more realistic measure of job availability to residents. Our findings reveal that, despite investments in public transportation and infrastructure, spatial mismatch in Medellín increased between 2012 and 2017. Additionally, the analysis shows that the greatest loss in job accessibility over time occurred for private transport, suggesting that the expansion of public transport in Medellín may have mitigated spatial mismatch.

Keywords: Spatial mismatch, job accessibility, travel times, transport costs, public and private transport

JEL Classification: J61, R41, R42

1 Introduction

Spatial disconnection from jobs can lead to poor labor market outcomes in cities, such as reduced labor earnings, a low employment rate, and low-quality jobs. In contrast, job accessibility, reduced travel times, and lower job search costs improve local labor market conditions (Ong & Blumenberg, 1998). The negative relationship between spatial disconnection from jobs and beneficial labor market outcomes has been called the Spatial Mismatch Hypothesis (SMH) (Gobillon, Selod, & Zenou, 2007; Kain, 1968). To address spatial mismatch and design public policies that improve access to jobs, it is essential to properly measure it and understand its extent.

In this paper, we propose a methodology to calculate spatial job mismatch and measure its spatiotemporal changes at the intra-urban level in a setting with incomplete data. We follow the literature that measures spatial mismatch through job proximity, directly measuring the degree of mismatch between the location of jobs and the residence of workers.[1] The studies measuring spatial mismatch based on job accessibility consider travel time or distance as the sole travel impedance. Still, monetary transportation costs, such as ticket fares, fuel costs, and parking fees, are also important determinants of job accessibility (Cui & Levinson, 2018, 2019; El-Geneidy et al., 2016; Liu & Kwan, 2020a). Our spatial mismatch measure improves the assessment of job accessibility by including monetary expenses and opportunity costs in overall transportation costs, correcting possible overestimates of accessibility via private transportation due to higher average speeds and lower travel times compared to public transportation (Liu, Ceder, Bologna, & Cabantous, 2016). In addition, we propose an adjustment to the spatial mismatch measure that considers incomplete information associated with dif-

[1] According to Houston (2005), there are four primary methodologies for measuring spatial mismatch in the literature: analyzing the labor market impacts of residential segregation, comparing commuting times, comparing earnings, and using measures of job proximity. The latter methodology has been widely used since the mid-1990s. It is more transparent and has a stronger conceptual footing than the other methodologies since it relies on a measure of job proximity to approximate the spatial mismatch (Holzer, 1991; Preston & McLafferty, 1999; Wang, Wu, & Zhao, 2022).

ferent zones observed when comparing job accessibility over time. When, for example, there is data on more zones in later periods, accessibility may mechanically increase over time because these zones may have jobs that were previously unaccounted for. We define an adjusted spatial mismatch measure, which weights by the number of destination zones each year, allowing for the analysis of the spatiotemporal changes of job accessibility without discarding data.

We apply our proposed methodology to measure spatial mismatch and its dynamics in Medellín, Colombia, a developing-country city. Medellín is an attractive case for analyzing spatial mismatch, as developing countries like Colombia are characterized by significant income inequality and a prevalence of low-quality jobs, both of which are exacerbated by spatial mismatch (Duque, García, Lozano-Gracia, Quiñones, & Montoya, 2023; Oviedo, Scholl, Innao, & Pedraza, 2019; Pinto, Loureiro, de Matos Sousa, & Motte-Baumvol, 2023). Compared to the capital city of Bogotá, Medellín has a well-developed metro system. The city has made significant public transport and infrastructure investments over the last decade but still has substantial poverty and urban segregation by income (Bocarejo et al., 2014). Travel times in the city have been increasing for all transportation modes. In 2012, an average trip in Medellín took 33 minutes. By 2017, that time increased to 36 minutes (Medellín Cómo Vamos, 2017).

In addition, there are institutional factors in Colombia's cities that may contribute to spatial mismatch. One of these is the stigmatization of some neighborhoods that are perceived as disadvantaged. These neighborhoods are regularly located at cities' outskirts and have poor accessibility, limited transport infrastructure, precarious socioeconomic conditions, high levels of crime, and excess low-skill labor supply. Employers discriminate against job applicants from these neighborhoods because they believe that people living in these places have unfavorable characteristics (e.g. poorer, less educated, less work experience) and have long commuting times, signaling low productivity (Diaz & Salas, 2020; Gobillon et al., 2007; Phelps, 1972; Zanoni, Acevedo, & Hernández, 2022; Zenou, 2002, 2013).

Our paper contributes to several branches of literature. First, it contributes to the empirical literature that uses job-access measures to study spatial mismatch. According to Holzer (1991), Houston (2005), and Wang et al. (2022), the limited availability of information about the spatial distribution of jobs and the distance/time and cost to reach them has led to conflicting results about the SMH. These data issues limit the robustness of job proximity measures. We use a measure of employment potential to calculate spatial mismatch, propose a methodology to fulfill all information requirements, and estimate a more robust measure of spatial mismatch, including travel times and transportation costs. Our proposed measure of spatial mismatch enables comparisons over time, allowing for analyses of its spatiotemporal evolution. The literature making such comparisons is scarce (Holloway, 1996; McLafferty, 1997; Preston & McLafferty, 1999). Therefore, this study attempts to contribute to the measurement of changes in spatial mismatch across space and time.

In addition, we contribute to the literature that measures the extent of spatial mismatch at the intra-urban level in Latin American cities. Most empirical studies measuring and testing spatial mismatch analyze U.S. and European cities. These studies have corroborated the negative relation between spatial mismatch and employment (Bastiaanssen, Johnson, & Lucas, 2022; Delmelle, Nilsson, & Adu, 2021; Taylor & Bradley, 1997), wages (Dauth & Haller, 2020; Delmelle et al., 2021; Stacy & Meixell, 2020; Zenou, 2009), and its positive relation with job-education mismatch (Di Paolo, Matas, & Raymond, 2017; Hensen, De Vries, & Cörvers, 2009). However, there is comparatively less evidence regarding SMH in developing countries, particularly in Latin America. Latin American cities present an urban context characterized by a significant proportion of the low-income population living in peripheral areas with poor access to opportunities, especially jobs. In addition, the high concentration of employment in central areas, combined with inadequate public transportation networks serving low-income neighborhoods, creates significant barriers for vulnerable groups seeking job opportunities (Vargas et al., 2017). In these settings, spatial mismatch may exacerbate income inequality and the prevalence of unemployment and low-quality jobs, further entrenching social and economic disparities. (García, Badillo, & Aristizábal, 2024; Pinto et al., 2023). Some evidence of spatial mismatch in Latin America is provided by the studies of Bocarejo and Oviedo (2012) in Bogotá (Colombia), Boisjoly, Moreno-Monroy, and El-Geneidy (2017) and Haddad and Barufi (2017) in São Paulo (Brazil), Hernandez, Hansz, and Massobrio (2020) in Montevideo (Uruguay), and Herszenhut, Pereira, da Silva Portugal, and de Sousa Oliveira (2022) in Rio de Janeiro (Brazil). These studies used measures of cumulative job opportunities in the case of public transport, finding that job accessibility is unevenly distributed by income, with low-income people in periphery areas presenting low levels of accessibility. Our paper aims to contribute to this literature by showing new evidence of spatial mismatch in a Latin American city, Medellín (Colombia).

The rest of this paper proceeds as follows: Section 2 presents the relevant literature on the different methods for measuring spatial mismatch. Section 3 describes our procedures to measure spatial mismatch. Section 4 describes the data and its limitations. It also presents descriptive statistics on travel times and jobs. Section 5 analyzes the accessibility measure computed for 2012 and 2017 and its evolution over time. Last, Section 6 summarizes our findings.

2 Literature review

The empirical literature quantifying spatial mismatch has evolved from using indirect indicators to direct measures (Houston, 2005). Initially, these measures were related to residential segregation (Kain, 1968; Leonard, 1987), residential suburbanization (Price & Mills, 1985), and employment suburbanization (Naudé, 2008), and were intended as an indicator of job proximity. This literature suggested that if workers living in poorer neighborhoods had to travel farther to reach jobs than those living in wealthier communities, and if there was a negative relationship between commuting times and job proximity, this would provide evidence of spatial mismatch (Gabriel & Rosenthal, 1996; Holloway, 1996; Holzer, 1991; McLafferty & Preston, 1992).

However, these earlier studies did not consistently find evidence of spatial mismatch in employment. While some of them found evidence of mismatch (Ihlanfeldt & Sjoquist, 1990, 1991), others reported an insignificant relationship between commuting times and job proximity (Ellwood, 1986), and some found a positive correlation (Cooke & Ross, 1999; DeRango, 2001). Subsequent literature suggested that these differing results could be attributed to the fact that commuting times or distances often overlook that many disadvantaged workers have a limited job search radius. These may be low-skilled or low-income workers living in distant neighborhoods (Gordon, Kumar, & Richardson, 1989; Holzer, Ihlanfeldt, & Sjoquist, 1994; Ihlanfeldt, 1993), women who have a lower propensity to commute because they prefer to stay close to home to balance work and family responsibilities (Borghorst, Mulalic, & Van Ommeren, 2024; Casado-Díaz, Simón-Albert, & Simón, 2023; Cooke, 1997; Hanson & Pratt, 1988), or workers who may have limited information about job opportunities beyond their neighborhoods. As a result, they often find employment locally, leading to shorter commutes for these groups.

Since the mid-1990s, studies have used direct measures to investigate spatial mismatch (Houston, 2005). These studies integrate travel times into job accessibility measures to analyze the location of job opportunities relative to the location of available workers (Preston & McLafferty, 1999). A common approach in this literature is to use a cumulative measure of job opportunities as a proxy of spatial mismatch (Geurs & van Wee, 2004; Hansen, 1959; Wang et al., 2022). This measure is straightforward to interpret, as it counts the number of jobs reachable from a specific region within a designated travel time threshold.

However, these measures of spatial mismatch rely solely on travel time and fail to account for the financial barriers that inhibit job accessibility, particularly transportation costs. As shown by Lucas (2012), El-Geneidy et al. (2016), and Liu and Kwan (2020a), the costs of transit are a significant obstacle for low-income individuals, hindering their ability to mobilize for job opportunities.

Few studies have considered both travel times and transport costs in measuring job accessibility. Bocarejo and Oviedo (2012) introduced a cumulative job opportunity function that includes generalized travel costs (impedance), factoring in a travel time budget and an affordability component. Their analysis of job accessibility in Bogotá (Colombia) offered a more nuanced view of transport options based on individual income, improving upon measurements that only use travel times. However, this approach demands extensive data to assess job accessibility across all city zones, requiring measures of transport costs for various modes, locations, and income levels to estimate generalized travel costs.

El-Geneidy et al. (2016) compare various accessibility measures, including travel time and travel fare, and discuss the implications of integrating different travel costs into the overall cost of travel. They express travel costs as the product of the minimum hourly wage and travel time plus the transit fare to travel between zones. This approach allows the proposed measure to calculate the number of jobs accessible on an hourly wage. This study shows that excluding transport costs from accessibility measures leads to overestimating job accessibility. Similarly, studies by Ma, Masoud, and Idris (2017) in Kelowna (Canada), Cui and Levinson (2018, 2019) in Minnesota and Minneapolis (USA), Liu and Kwan (2020a, 2020b) in Chicago (USA), and Herszenhut et al. (2022) in Rio de Janeiro (Brazil) confirmed the importance of considering monetary costs in measuring job accessibility.

We follow a similar approach to El-Geneidy et al. (2016), including monetary costs as a constraint to job accessibility. We also consider the differences in travel costs for public and private transportation, recognizing that public transit may often be more affordable. Understanding affordability is vital for addressing transport inequality in cities in the Global South

(Bocarejo & Oviedo, 2012; Herszenhut et al., 2022). Our study provides an accessibility measure that incorporates travel costs and factors in the affordability of different transportation modes.

Most studies measuring spatial mismatch are based on cross-sectional data. Only a few studies, such as those by Jin and Paulsen (2018), Qi, Fan, Sun, and Hu (2018), and Pereira (2018), have examined the evolution of spatial mismatch over time. These studies calculate spatial mismatch using a fixed set of spatial units, such as census blocks, which do not change in number or boundaries over time. In contrast, our study analyzes transportation zones, which tend to change over time due to various factors, such as shifts in points of interest within a city and changes in public transport coverage.

Recent studies that use transportation zones as geographic unit analysis (de Castro, Loureiro, & Giannotti, 2025; Haddad & Barufi, 2017; Luz, Barboza, Portugal, Giannotti, & Van Wee, 2022, among others) often do not consider how spatial changes in these units over time may impact their findings. We contribute by proposing an adjusted accessibility measure that considers the differences in spatial units over the years. This approach allows us to analyze spatiotemporal changes in job accessibility without discarding data from zones that change over time.

3 Methodology

Our empirical approach to measuring job accessibility considers two key variables: the employment level in workplace zones and travel times between zones. In the following subsections, we describe the measure of job accessibility and how we calculate the components associated with employment levels, transport costs, and travel times. In addition, we propose an adjustment to the job accessibility measure, which allows comparison across years when the number of observed zones varies over time.

3.1 Job accessibility measure

To measure job accessibility, we use a weighted measure of access to employment, where travel times are the weighting factor. We use a Hansen equation (Hansen, 1959) to measure accessibility, adapted from Di Paolo et al. (2017). This measure captures both transport accessibility and the opportunity cost of travel time. The Hansen equation is analogous to measures of residential commuter market access in quantitative urban models, such as Tsivanidis (2023), with jobs at each destination drawing job-seekers to a workplace:

$$A_{i,m,t} = \sum_{j} \frac{jobs_{j,t}}{r_{i,j,m,t} \times \bar{w}_t + c_{i,j,m,t}}, \quad r_{i,j,m,t} > 0, \tag{1}$$

where, $A_{i,m,t}$ is the accessibility in zone i and year t, using transportation mode m (private vehicle, p; or public transport, pb); $jobs_{j,t}$ is the number of jobs in zone j in year t; $r_{i,j,m,t}$ is the travel time in minutes from zone i to j using mode m in year t; $\bar{w}_t$ is the average wage per minute in t; and $c_{i,j,m,t}$ is the monetary transportation cost from i to j using transport mode m in year t .[2]

Our accessibility measure is the number of jobs accessible in a ratio of 1 monetary unit from an origin. Specifically, if the denominator is in dollars or in Colombian pesos as in our application, $A_{i.m,t}$ quantifies how many jobs are in a 1 dollar (1 peso) travel cost circle centered on an origin in zone i through transport mode m in year t.[3]

Since our measure counts the number of jobs accessible per monetary unit starting from a given location, it is a primal, location-based, and active measure (Levinson & Wu, 2020).

[2] In this measure employment at each destination acts as a "pull factor" that draws job seekers to particular destinations (Bahar, 2024). This factor is weighted by the inverse of travel costs to a destination. The Hansen equation measure does not consider wages at the destination to estimate accessibility. We only use city-wide wages to measure the opportunity cost of time when calculating travel costs.

[3] We choose to calculate accessibility in terms of jobs per monetary unit of travel cost instead of jobs per minute of travel to better capture the differences in accessibility between public and private transport. This approach also allows for the straightforward inclusion of monetary transport costs. On a time basis, private transportation consistently offers higher accessibility due to its higher average speed.

Moreover, our measure explicitly considers travel modes to each destination. The monetary and non-monetary costs of travel act as the impedance to reaching jobs.

3.2 Adjusted job accessibility measure

Equation (1) is not suited to analyze the evolution of spatial mismatch in an incomplete data context, where zones are not observed in both years or change spatial boundaries. If there are more observed zones in the latter year, accessibility may go up mechanically because the employment in previously unobserved zones did not appear initially.

We propose an adjusted measure that allows us to compare accessibility across years, even if the number of observed zones varies over time. We define adjusted accessibility as:

$$\hat{A}_{i,m} = A_{i,m,t} \times \frac{1}{n_t}. \tag{2}$$

Here, n_t is the number of zones in period t that are destinations for trips starting in zone i. The measure $\hat{A}_i$ is the average number of jobs found in a radius of one monetary unit by traveling to a single destination zone. It contrasts with unadjusted accessibility, which counts jobs in every possible destination zone. Adjusted accessibility weights by the number of zones observed each year.

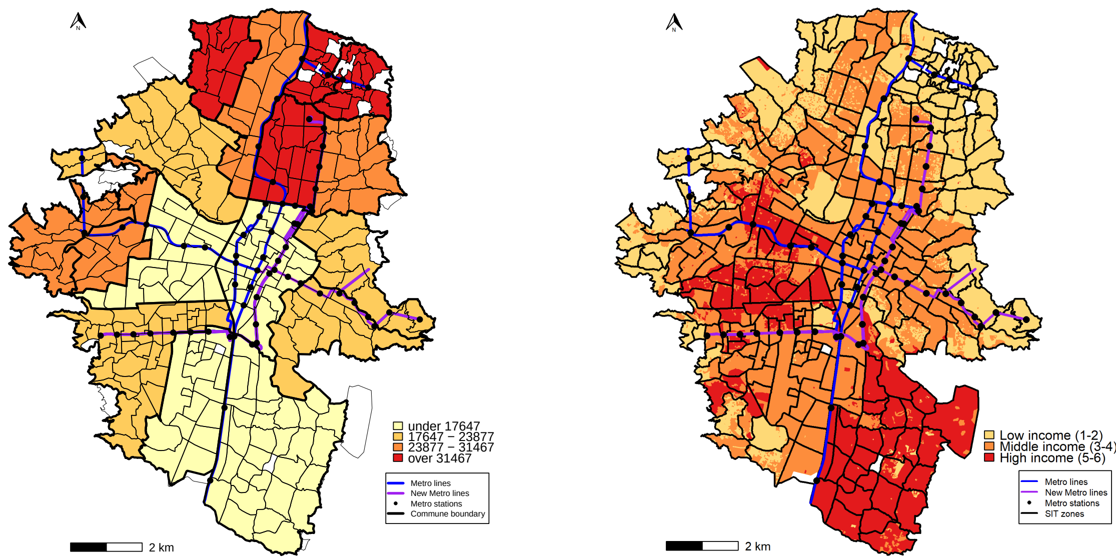
4 Study area, data, and descriptive statistics

4.1 Study area: Medellín

Medellín is located in the northwestern part of Colombia and is the second-largest city in the country after Bogotá, the capital. Its population is around 2.5 million and has an extension of 380 km^2 (DANE, 2018), which implies a density of 6597.7 inhabitants per km^2. In this study, we analyze the urban area of Medellín, which is divided into 16 communes and 275 neighborhoods. Our primary spatial units of analysis are the Integrated Transport System zones, SIT zones (for its acronym in Spanish, *Sistema Integrado de Transporte*). These zones delimit the area of influence of the transportation system in Medellín and consist of homogeneous regions, smaller than neighborhoods, defined in terms of land use, points of interest, and future expansion projects proposed in the city's Territorial Arrangement Plan (Área Metropolitana del Valle de Aburrá and Universidad Nacional de Colombia, Sede Medellín, 2012). A distinctive feature of Medellín compared to other cities in Colombia and Latin America is its public transportation system, the Metro system. This system has significantly increased accessibility throughout the city, particularly in remote and low-income zones (Bocarejo et al., 2014). The Metro system started in 1995 with an elevated metro line, and by 2019, it transports around 1.5 million passengers daily (Metro de Medellín, 2019). It has two elevated train lines, five lines of aerial cable cars (*Metrocable*), one tram line, two lines of BRT (*Metroplus*), one electric bus line, and several private bus routes.

Figure 1 shows the spatial distribution of population density and income levels in Medellín. We observe that the largest and most densely populated regions in Medellín are in the north and southwest of the city (Panel a). The north of the city has a low-income population and relatively well-equipped transportation infrastructure in terms of access to the Metro system (Panel b). In contrast, the city's wealthiest areas, predominantly in the south, have low density and few Metro system stations.

Figure 1. Study area: Medellín



(a) Population density by commune (people per km^2) (b) Income distribution by block

Notes: These maps show population density at the commune level and income at the block level. SIT zones are also depicted on each map. The population density data is for 2017. The income level by blocks corresponds to socioeconomic strata, which are categories defined by the Colombian government to assign social programs and subsidies (1 = very low income to 6 = very high income).

Source: Own calculation with official information from the Geomedellin database (www.medellin.gov.co/geomedellin).

4.2 Origin, destination, and travel time data

Our data comes from Medellín's Origin-Destination survey (EOD, for its acronym in Spanish, *Encuesta Origen-Destino*) for 2012 and 2017. This cross-sectional survey provides individual-level information on mobility patterns by trip purpose (work, study, home, health, and shopping), means of transportation used (Metro, Metroplus, Metrocable, bus, car, taxi, bicycle, motorbike, and walking), travel times, trips, and demographic characteristics. The information in the EOD survey is representative at the SIT zone level; there were 261 SIT zones in 2012 and 306 SIT zones in 2017. The average SIT zone has an area of 0.33 km^2.

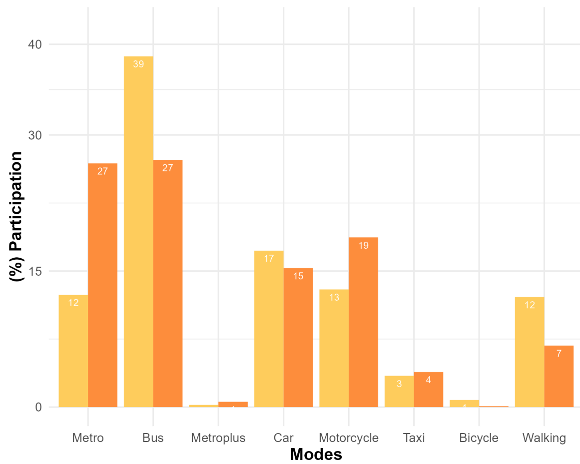
The EOD surveys show that between 2012 and 2017, there was an increase in the daily number of journeys made in the city, from 5,614,292 daily trips in 2012 to 6,131,727 daily trips in 2017, a 9.2% growth. Similarly, the percentage of people who travel daily went from 69% to 74% between 2012 and 2017. The average travel time also increased: in 2012, it was 33 minutes, and in 2017, it reached 36 minutes.

Figure 2, panel (a), shows that the share of trips by metro expanded from 12% in 2012 to 27% in 2017, while the share of bus trips decreased from 39% to 27%. For private transportation modes, travel by private car reduced its participation from 17% in 2012 to 15% in 2017, while travel by motorcycle went from 13% to 19%. Walking trips saw a decrease by 4 percentage points, from 12% in 2012 to 7% in 2017.

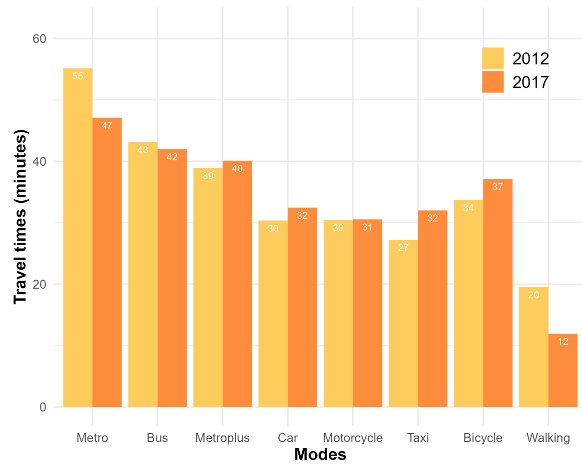
Regarding the average travel time, Figure 2, panel (b) shows that reported travel time increased for almost all private transportation modes, with reported travel time increases between 1 minute and 5 minutes. The largest increases in average reported travel time occurred for taxi (27 minutes in 2012 vs 32 minutes in 2017), bicycle (34 minutes vs 37 minutes), and cars (30 minutes vs 32 minutes). A few modes experienced a reported travel time decrease: Metro travel times went from 55 minutes to 47 minutes, and bus travel times went from 43 minutes to 42 minutes.

An outstanding question is the extent to which changes in mode choice contribute to the observed variations in accessibility measures. Changes in the share of trips using private transportation modes such as taxis or motorcycles may have contributed to increased travel times via congestion. Moreover, the changes in accessibility may induce further changes in mode choice and job search behavior. Patacchini and Zenou (2005) show that job search behavior varies depending on transportation mode choices.

Figure 2. Travel participation and average travel times by mode



(a) Travel participation



(b) Average travel times

Notes: These figures show the travel participation and average travel times by mode of transportation in Medellín between 2012 and 2017. See Appendix A and Appendix Tables A1 and A2 for details about the classification of travel modes.

Regarding congestion, the Global INRIX Traffic Scorecard (INRIX, 2022) shows that Medellín is one of the most congested cities in the world. According to INRIX (2022), in 2017, Medellín ranked as the 18th most congested city in the world and the 3rd in Latin America, with a total of 57 hours lost in traffic during peak conditions compared to off-peak conditions on average. This congestion level placed Medellín after Sao Paulo (Brazil) and Bogotá (Colombia). By 2022, the number of hours lost in Medellín increased to 91h, with an average speed in the downtown area of 12 miles per hour (mph). González (2009) and García, Posada, and Corrales (2016) attribute these low speeds to a saturated transportation network and transit routes converging downtown.

The increase in the number of trips and the share of usual travelers suggest that Medellín faced a high demand for transportation in the analysis period. As a result, the transportation infrastructure may not have been able to support this demand, making mobility one of the city's major challenges (García et al., 2016; Sanchez et al., 2019).

4.3 Computing travel times for 2012 and 2017

The reported travel times discussed above are only available for trips in the EOD survey. However, our accessibility measure requires travel times between every pair of zones for all transportation modes. We now describe how we compute these travel times.

We use different methodologies for each year and each transportation mode. We have two years in our sample: 2012 and 2017. For 2017 we used the Google Distance Matrix API to compute commuting time by public transport (any combination of bus and metro system) and the Bing Maps Distance Matrix API to compute commuting time by private vehicle (cars and motorbikes).[4]

For 2012, our travel time data is incomplete because neither the Google nor Bing APIs provide historical travel times for that year. Therefore, when travel times between a pair of zones i, j are available from origin-destination surveys for the two years, we set travel time from zone i to zone j by transport mode m for 2012 ($r_{i,j,m}(2012)$), as the product between the times calculated for 2017 ($r_{i,j,m}(2017)$) and the variation on survey-reported times between 2017 ($sr_{i,j,m}(2017)$) and 2012 ($sr_{i,j,m}(2012)$). When survey-reported travel times are not available, we impute earlier travel times based on commune-level changes.[5] Specifically, we impute travel times for 2012 between a pair of zones from 2017 values using the average growth rate of travel times between the two years for each commune

[4] For this 2017 data, we calculate origin-destination travel time matrices using the centroids from each zone. We set the departure time at 7 A.M., the beginning of the morning rush hour. Using data from the OD survey for 2012 and from the Google API for 2017 introduces a potential comparability issue. The 2017 times are computed for the morning rush hour, while the 2012 times are for any time of the day. We believe this is not a significant issue. Travel times between morning and evening rush hours are similar, and trips in rush hours are about 72% of total trips to work in 2012 and 79% of trips to work in 2017.

In Appendix Table B3, we recalculate our accessibility measures for 2012 using only trips from 5 to 9 A.M. We use this extended rush-hour time interval to retain data for as many origin-destination pairs as possible: the difference in average travel times from 5 to 9 A.M. and 7 to 9 A.M. is not statistically significant. The measures remain virtually unchanged when we use this rush hour data for 2012.

[5] Our dataset incorporates expansion factors to ensure representativeness by extrapolating sample responses to the target population. These expansion factors were designed to adjust for sampling biases and accurately reflect the population distribution. On average, an origin-destination pair includes approximately 201 individuals in 2012 and 133 individuals in 2017.

$(1 + \Delta\overline{sr}_{m,h(i)})$, where $\Delta\overline{sr}_{m,h(i)} = (\overline{sr_{m,h(i)}}(2017) - \overline{sr_{m,h(i)}}(2012))/\overline{sr_{m,h(i)}}(2012)$, and where $\overline{sr}_{m,h(i)}(t) = \frac{1}{z_{t,h(i)}} \sum_j \sum_{i \epsilon h(i)} sr_{i,j,m}(t)$ represents the mean of reported times in the commune $h(i)$ in period t, $z_{t,h}$ is the number of commutes which origin is in commune $h(i)$ during period t, and finally $sr_{i,j,m}(t) = \frac{1}{K} \sum_k sr_{i,j,m,k}(t)$ where K represents the number of trips. Our final travel time measure is:

$$r_{i,j,m}(2012) = \begin{cases} r_{i,j,m}(2017) - (sr_{i,j,m}(2017) - sr_{i,j,m}(2012)) & \text{if data on } sr_{i,j,m} \text{ is available,} \\ r_{i,j,m}(2017)(1 + \Delta\overline{sr}_{m,h(i)}) & \text{if data on } sr_{i,j.m} \text{ is not available.} \end{cases} \tag{3}$$

To compute travel times inside the same zone ($r_{i,i,m}$), we calculate the average travel time from each zone's centroid to its edge. For each zone i, let $R_{i,outside}$ denote the radius of the smallest circle that contains it. Also, let $R_{i,inside}$ denote the radius of the largest circle contained in it, and AVS_m is the average travel time using transportation mode m. Then, travel time inside the same zone is:

$$r_{i,i,m}(t) = \frac{R_{i,outside} + R_{i,inside}}{2} * AVS_m. \tag{4}$$

We use different approaches depending on the year analyzed to compute travel times by transportation mode. For 2012, we follow Equation (3), which uses a combination of times computed with mapping apps and survey-reported data from the EOD. For 2017, we calculate travel times for public and private transportation through the road network using the Google and Bing APIs, respectively.

Table 1 shows the average computed and survey-reported travel times by transport mode each year. We note that there are differences between computed and reported travel times. The Table shows that both computed and reported travel times increased for all transport modes between 2012 and 2017. Based on computed travel times, it took approximately 20 minutes to commute to work using private transport and 48 minutes using public transport in 2012. By 2017, these commuting times had increased to 25 and 55 minutes, respectively. These results imply an increase of 27% in travel times in private transport and 14% in public transport, which may be associated with increases in congestion levels in the city (García et al., 2016; Restrepo, 2012).

Table 1. Computed and reported travel times (minutes)

A. Computed travel times				
Transport mode	Mean 2012	Mean 2017	Diff means 2017-2012	% Diff means 2017-2012
Private	19.50	24.87	5.37	27.53%
Public	48.32	55.08	6.76	13.99%
B. Reported travel times				
Private	25.06	30.73	5.67	22.62%
Public	39.14	47.94	8.80	22.48%

Notes: Panel A shows computed travel times calculated using Equation (3). These computed travel times come from an origin-destination matrix where each trip is counted once. Panel B shows travel times reported by individuals in EOD, where only one trip is counted per person. The last two columns show the level and the percentage difference in mean travel times between 2017 and 2012. Computed travel times take into account all the possible trips in the origin-destination matrix, while reported travel times only consider the trips that are reported in the EOD survey.

Figure 3 shows computed average travel times by SIT zone calculated at the origin level. This Figure shows that for private transport, travel times tend to be higher in the outskirts of the city, and for public transport, lower travel times are located in the center of the city where the metro line expansion may have increased public transit services.[6] We also notice

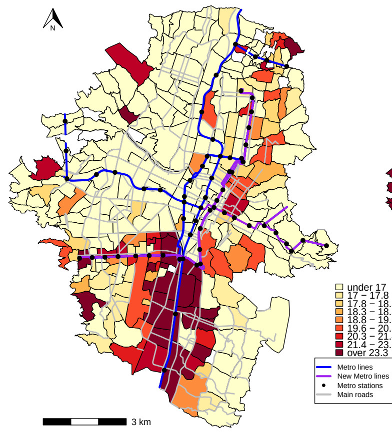
[6] A limitation of our analysis is that we lack data on potential sources of variation in travel times by public transport associated with changes in transport services, such as the number of lines or the frequency of buses/trains. Such changes in services could also affect travel times.

increased travel times for public transport in the southwest of the city, where there was also investment in public transport infrastructure. These increases in travel times, even though some areas of the city received public investment in transport, seem to indicate a certain inefficiency of this transport policy, as has occurred in other cities in developing countries (Brooks & Denoeux, 2022; Gaduh, Gračner, & Rothenberg, 2022). However, it is important to note that different sources may increase demand for the transport system in Medellín. For instance, the growth in population, jobs, car usage, or commuting flows in the municipalities surrounding Medellín.[7] In these municipalities, according to data from DANE (2018), the population growth rate between 2012 and 2017 was 9.1%, and according to data from the origin-destination survey, the percentage of trips to Medellín was 26.7% in 2012 and 33.9% in 2017, increasing by 7.2 percentage points. Therefore, these increases in population and trip flows from neighboring municipalities could be generating important pressures on Medellín's transportation system, which, without the expansion of the transportation system, could imply a greater overload of its capacities and increased congestion levels.

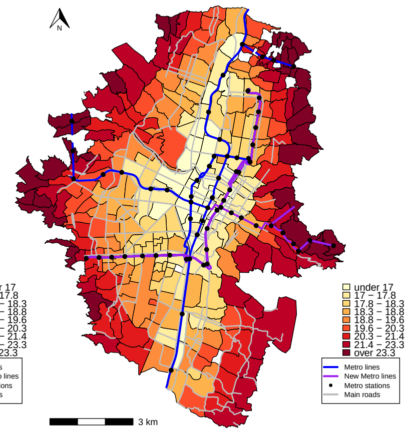
[7] The municipalities surrounding Medellín correspond to Caldas, La Estrella, Sabaneta, Itagüí, Envigado, Bello, Copacabana, Girardota, and Barbosa.

Figure 3. Spatial distribution of computed average travel times at the origin by transport mode

Private transport

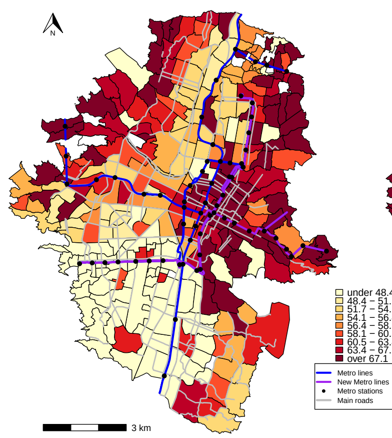


(a) 2012

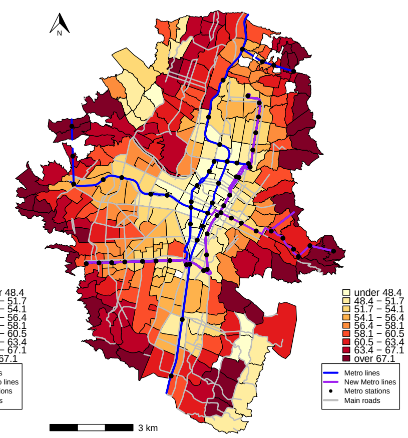


(b) 2017

Public transport



(c) 2012



(d) 2017

Notes: These maps show the computed average travel times (in minutes) at the origin by transport mode and year. There were 261 SIT zones in 2012 and 306 SIT zones in 2017.

4.4 Travel costs

Our measure of travel cost associated with travel time is the product of travel times and wages, as in equation (1). We use the *Encuesta de Calidad de Vida* (ECV) to retrieve data on the average monthly wage.[8]

We estimate the monetary transportation cost for each transportation mode. For public transport, we use the price of one metro system ticket, $farecost_t$ (fares between the metro system and private buses are similar). In 2012, the fare price was 1600 COP, or about 1.3 USD, using a PPP exchange rate. In 2017, the price was 2000 COP, about 1.5 USD in PPP.[9] Longer trips usually require connections with an additional ticket. To account for this extra cost, we compute the relationship between traveled distance and the number of fares.[10] In Appendix Figure B4, we show that this relationship is approximately linear in both years. Therefore, first, we estimate a linear regression of the number of fares on trip distance. Then, we multiply the predicted number of fares from this linear regression by the fare cost.

We estimate private transport costs as the product of public transportation costs, $c_{i,j,public,t}$, and the ratio between private transport and public transport expenses, δ=2.18, obtained from Colombia's 2016-2017 National Budget Survey (DANE). To summarize, the monetary transportation costs for public transport ($c_{i,j,public,t}$) and private transport ($c_{i,j,private,t}$) are given by the following equations:[11]

[8]To convert it into a wage per minute, we use the fact that in Colombia, full-time employees were legally required to work 48 hours per week in both 2012 and 2017. Assuming a person works $48 \times 4 = 192$ hours per month, we compute the wage per minute by dividing the monthly wage by 192×60. This resulted in an average of 90.1 pesos in 2012 and 96.2 pesos in 2017.

[9]OECD PPP USD/COP exchange rates were 1215 Colombian pesos for 2012 and 1328 Colombian pesos for 2017. The nominal exchange rates were 1798 for 2012 and 2951 for 2017.

[10]We do not explicitly observe the number of fares paid in the data, but we do observe when trips require different vehicles (e.g., metro + bus). We consider an additional vehicle to be an additional fare.

[11] Our results about the evolution of accessibility and adjusted accessibility are robust to allowing the number of fares to change discontinuously with trip distance by public transport. In Appendix Tables B1 and B2, we calculate our measures of accessibility, allowing the number of fares to be one below a threshold and two above it. For private transportation, since costs do not change discontinuously at a distance threshold, we smooth the relationship between private cost and trip distance after multiplying the public cost by δ. We show results varying this distance threshold. A larger distance threshold for payment of an additional fare in public transportation increases public accessibility (since public transportation becomes cheaper) and private accessibility (since we calculate private transportation costs based on public transportation costs).

$$fares_{i,j,public,t} = \beta_{0,t} + \beta_{1,t} dist_{i,j} + \epsilon_{i,j,public,t}, \tag{5}$$

$$c_{i,j,public,t} = farecost_t \times (\hat{\beta}_{0,t} + \hat{\beta}_{1,t} \times dist_{i,j}), \tag{6}$$

$$c_{i,j,private,t} = \delta \times c_{i,t,public,t}. \tag{7}$$

4.5 Jobs data

We now describe how we recover information on the number of jobs at each destination from labor and origin-destination surveys. Employment levels at the residence level and job totals at the workplace level are calculated using household and firm surveys. However, for our application, these surveys only have employment data for larger geographical units (e.g., cities or regions), and they do not provide employment nor jobs information at finer geographical levels. To solve this problem, we assume that the number of jobs at each destination i is proportional to the number of trips to work at this destination within each larger geographical unit h, where each larger area h may contain multiple destinations i. We then approximate the spatial distribution of jobs using the following formula:

$$jobs_i = jobsTotal * \frac{W_{h(i)} * jobsODC_{h(i)}}{\sum_h W_h * jobsODC_h} * \frac{jobsOD_i}{\sum_{i \epsilon h(i)} jobsOD_i}. \tag{8}$$

Here, $h(i)$ is the larger geographical unit that contains destination i, $jobs_i$ is the number of jobs in the zone i, and $jobsTotal$ is the total number of jobs in the city. The variable W_h is the survey weight for the geographical unit h. The variables $jobsODC_h$ and $jobsOD_i$ are the number of trips to work at h (where i belongs) and the number of trips to work to destination i, respectively.[12] In our application, the smaller geographical units i are transportation zones,

[12]We count just one trip to work per person.

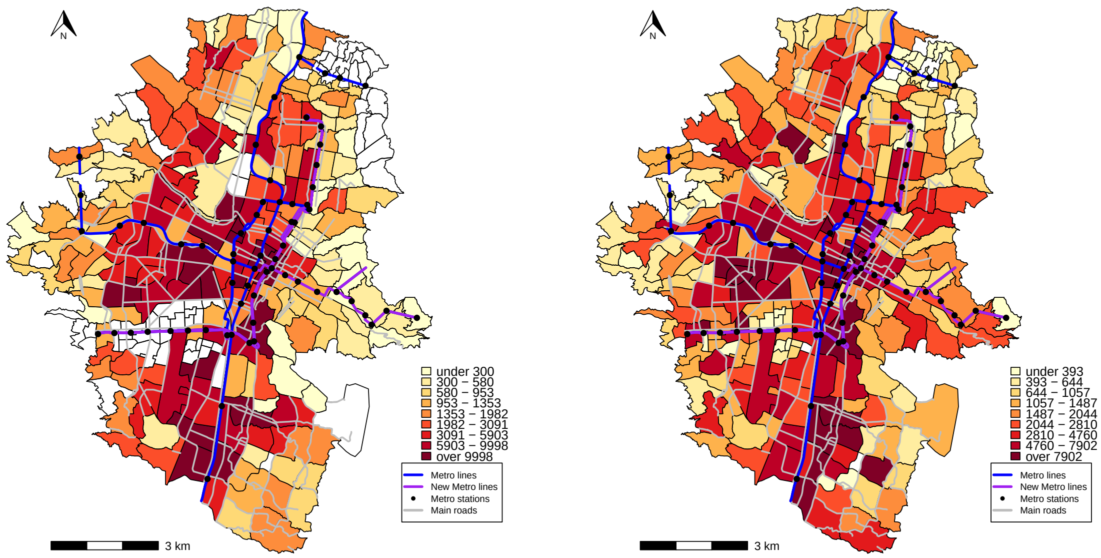
and the larger ones h are communes akin to New York boroughs.

Figure 4 shows the spatial distribution of jobs calculated at the SIT zone level for 2012 and 2017.[13] We observe high job density in areas around the Metro system. Between 2012 and 2017, the number of jobs increased along the new Metro system lines in the city's east, center, and northwest. The highest job counts are concentrated in the city's south and center, which aligns with expectations: Medellín's center serves as the city's commercial hub, while the southern region is industrial and hosts financial and entertainment services. This polycentric structure in Medellín is consistent with the results found by Galeano (2013) and Rodríguez and García (2014), who identify that commercial activities and tourist and business services are the sectors with the highest labor demand in the city and concentrate in the south and center. Moreover, Medellín's polycentric urban structure is similar to that found in other Latin American cities (Fernández-Maldonado, Romein, Verkoren, & Pessoa, 2014).[14]

[13] According to the Gran Encuesta Integrada de Hogares (GEIH), between 2012 and 2017, employment in Medellín increased by 7%, from 1,024,055 workers to 1,100,509 workers.

[14] A limitation of our data is that we cannot readily separate salaried employment from non-salaried employment or self employment when counting the number of jobs in an area. If total jobs in an area are high only because of a large number of self-employed workers, we may be overestimating access to jobs in that area. Our data only separates "dependent" workers, who have standard labor contracts, and "independent" workers, who may be paid as contractors or be self employed. Figure B2 in the Appendix shows that the spatial distributions of dependent and independent jobs across the city are similar. This similarity supports our usage of total jobs as a correct representation of the spatial patterns of jobs in the city.

Figure 4. Spatial distribution of jobs



(a) 2012 (b) 2017

Notes: These maps show the spatial distribution of jobs for 2012 and 2017, Job density: jobs per km^2. Because of missing data and changes in SIT zones between years, some zones do not have assigned jobs (white areas in the maps). There were 261 SIT zones in 2012 and 306 SIT zones in 2017.

5 Results

This section presents the results for spatial mismatch measures in Medellín for 2012 and 2017 and their evolution over time. Our empirical approach assumes that there is always a spatial mismatch. This assumption is reasonable if we consider the mechanisms that explain the spatial mismatch presented by Gobillon et al. (2007). We show all of our results in terms of the accessibility measure, which is inversely related to mismatch.

Table 2 shows average job accessibility measures by transportation mode and year. The non-adjusted measure indicates that job accessibility is higher for private transportation than for public transport. In 2017, travelers could access an average of 175 jobs within a radius of 1 Colombian peso using private transport, compared to 180 jobs with public transport. In U.S. dollar terms, using the PPP exchange rate, this corresponds to approximately 232,400 jobs for private transport and 239,040 jobs for public transport within a radius of 1 USD. A comparison of the non-adjusted measure across years shows that job accessibility decreased in Medellín from 2012 to 2017, with a greater decrease observed for private transportation.

Table 2. Job accessibility measures

Transport mode	Mean 2012	Mean adjusted 2012	Mean 2017	Mean adjusted 2017	Diff adjusted 2017-2012	%Diff adjusted 2017-2012
Private	186.45	0.714	174.79	0.571	-0.143	-20.02%
		[0.703, 0.726]		[0.562, 0.579]		[-21.65%, - 18.54%]
Public	181.26	0.694	180.28	0.589	-0.105	-15.12%
		[0.684, 0.706]		[0.580, 0.598]		[-16.88%, - 13.58%]

Notes: This Table shows average job accessibility measures calculated using Equation (1) for the non-adjusted measure and Equation (2) for the adjusted measure. There were 261 SIT zones in 2012 and 306 SIT zones in 2017. Values in brackets represent 95% confidence intervals calculated by resampling jobs at the SIT zone level using a paired bootstrap with 1000 repetitions.

However, as previously mentioned, unadjusted job accessibility may be wrongly estimated over time due to changes in the number of SIT zones considered. The adjusted measure in Table 2 removes this effect. Using the adjusted measure, we still observe higher accessibility by private transportation. In 2017, in a radius of 1 Colombian peso (1 USD) and traveling to a single destination zone, an individual could reach 0.571 jobs (758 jobs) in private transport and 0.589 jobs (782 jobs) by public transport. Despite this, a comparison across years reveals a decline in job accessibility in Medellín between 2012 and 2017. The decrease in job accessibility is negative and statistically significant, with private transport experiencing a more considerable decline (20%) than public transport (15%).

To compare the results of our job accessibility measure with those of the traditional methodology without monetary costs, Table B4 in the Appendix shows the average accessibility and the adjusted measure excluding these costs. In general, we observe that travel-time accessibility measures estimate a higher number of jobs that can be reached than combined travel-time and monetary-travel-cost measures. For public transport, when only travel time is considered, the estimates of job accessibility are three and two times higher when monetary travel costs are included for 2012 and 2017, respectively. For private transportation, this overestimation is even larger (nine and seven times, respectively), likely due to its higher monetary travel costs relative to the average wages in the city, such as fuel, insurance, and maintenance. These results are consistent with those found in the literature that includes monetary travel costs in measures of job accessibility (Cui & Levinson, 2019; El-Geneidy et al., 2016; Herszenhut et al., 2022).

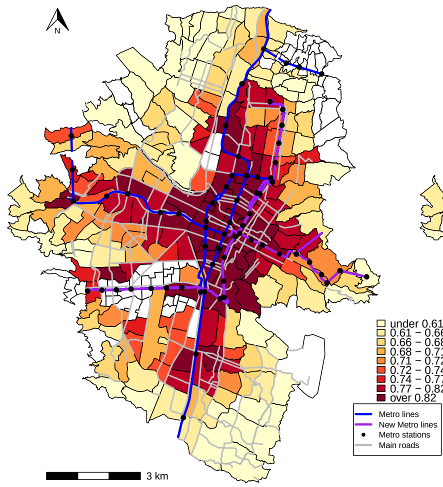
To account for sampling variation in our job measures, we obtain confidence intervals for the mean accessibility measures via bootstrapping. Specifically, we resample jobs data while preserving the dependency between jobs by SIT zones in 2012 and 2017. We first draw pairs of employment totals for the entire city each year, accounting for the sampling error in Colombia's labor survey. Next, we resample pairs of job shares by SIT. These pairs of job shares are resampled from the job distributions in the EOD survey, assuming a joint distribution with positive covariance between the number of jobs in 2012 and 2017. This ensures that if the jobs draw for a SIT zone in 2012 is high, it will also be high in 2017. Once we have the job shares by SIT for both years, we calculate their adjusted accessibility measure. Finally, we compute the mean across SIT zones of the accessibility measure. We repeated this procedure 1,000 times. We report a confidence interval based on the 2.5th and 97.5th percentiles of the distribution of iterations of the mean adjusted accessibility measure.

Figure 5 shows the spatial distribution of adjusted job accessibility.[15] We observe higher job accessibility (and lower spatial mismatch) in the center and south of the city where jobs are concentrated. By transport mode, we note that private transport offers higher job accessibility, particularly in peripheral areas. The differences in the spatial distribution of accessibility across years are subtle. Nevertheless, in Panel (b), accessibility appears more concentrated in zones such as the northwest instead of areas where new metro lines appeared in 2017. Hence, it seems that the metro system does not significantly impact the distribution of accessibility.

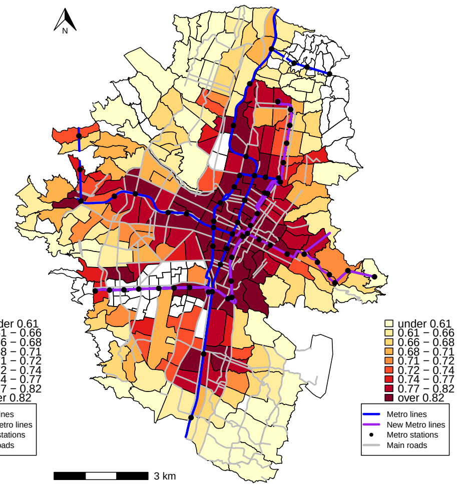
[15]We also show the distribution of unadjusted job accessibility in Figure B1 in the Appendix.

Figure 5. Adjusted job accessibility

2012

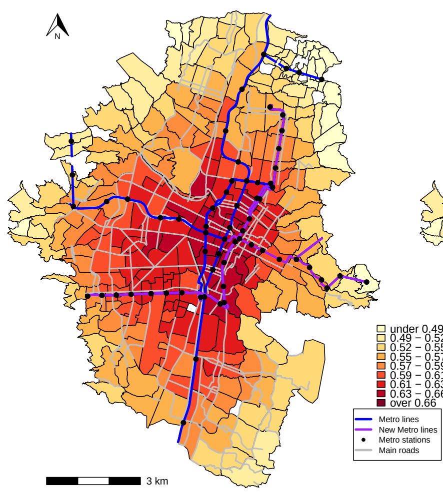


(a) Private transport

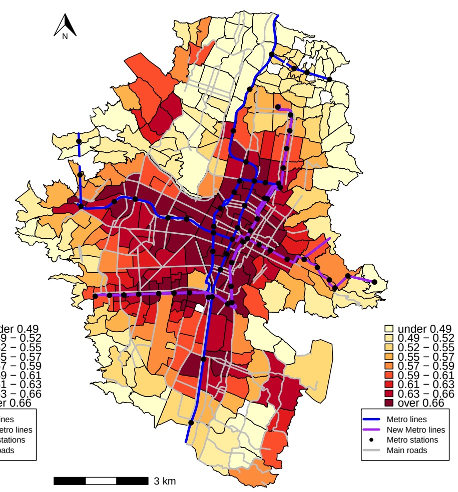


(b) Public transport

2017



(c) Private transport

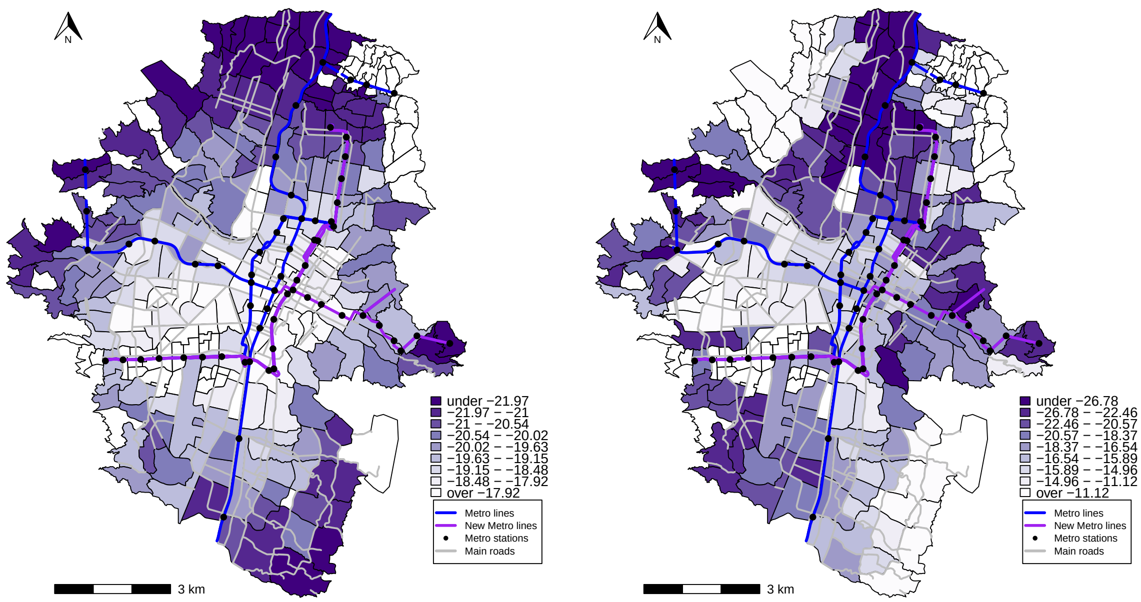


(d) Public transport

Notes: These maps show the adjusted job accessibility measure at the SIT zone level calculated using Equation (2) by year and transport mode. There were 261 SIT zones in 2012 and 306 SIT zones in 2017.

To analyze the evolution of spatial mismatch in the city, we calculate the percentage difference of the adjusted job accessibility measure between 2017 and 2012 by transport mode. Figure 6 shows that adjusted accessibility decreased universally across the city during this period. While employment increased by 7% between 2012 and 2017, the rise in travel times counteracted this growth, resulting in reduced accessibility in 2017. We do not observe clear evidence of improved accessibility in areas near the new metro lines. While we do not conduct a counterfactual analysis, the lack of observed improvement indicates that the new metro lines likely mitigated the decline in accessibility rather than directly enhancing it. Furthermore, Panel (b) reveals that public transport accessibility declined less sharply than private transport accessibility.

Figure 6. Difference in adjusted job accessibility between 2017 and 2012 (%)



(a) Private transport

(b) Public transport

Notes: These maps show the spatial distribution of the percentage difference of adjusted job accessibility between 2017 and 2012 by transport mode.

One possibility behind this decrease in accessibility between 2012 and 2017 is that population density changed unequally throughout the city, changing the distribution of jobs and accessibility even without changes in travel time. Appendix Figure B3 shows little spatial correlation between changes in accessibility and changes in population density. Moreover, density increased throughout the city from 2012 to 2017. If higher density were associated with a higher number of jobs and travel times remained constant, we would expect an increase in accessibility. Instead, accessibility decreased in all areas because of the higher travel times.

Another significant finding concerns the evolution of accessibility gaps between private and public transportation in both years. In 2012, the gap was 0.02; in 2017, it narrowed slightly to 0.018, with adjusted accessibility being higher for public transportation (see Table 2). Although overall accessibility declined for both modes, the relative difference shifted by 2017, making public transportation relatively more accessible. This reduction in the gap supports the hypothesis that public transit played a role in mitigating the rise in spatial mismatch within the city.

We extend this analysis to examine heterogeneity in job accessibility across job zones according to differences in the characteristics of their population. In Figures B5 and B6 in the Appendix, we relate the average of adjusted accessibility to the share of women and people in different age groups, respectively. Similarly, in Appendix Table B5, we calculate the average adjusted accessibility across zones by socioeconomic strata. The results do not show a clear relationship between the share of women and job accessibility at the zone level. This could indicate that there are no marked differences in accessibility levels by gender and that both men and women have experienced declines in job accessibility across the years we analyzed. Regarding the proportion of the population in each age group, Figure B6 shows a negative relationship between a higher proportion of young people (18-24 years) and job accessibility and a positive relationship between a higher proportion of middle-aged people (41-65 years) and job accessibility. These results may indicate that young people may face a greater spatial mismatch than middle-aged people, who may have had the opportunity to choose more central residence locations.

In terms of job accessibility levels by income, as measured by socioeconomic strata, Table B5 in the Appendix shows that high-income areas present the highest levels of job accessibility by private and public transport in both years. In contrast, areas classified as lower income have reduced levels of access to jobs. These results suggest that residents of socially disadvantaged areas in Medellín have less equitable accessibility to jobs, which is consistent with results found in other studies in developing city contexts (Bocarejo & Oviedo, 2012; Boisjoly et al., 2017; Hernandez et al., 2020; Herszenhut et al., 2022).

6 Conclusions

In this paper, we propose an alternative methodology to calculate spatial mismatch at the intra-urban level, which includes transportation costs arising from monetary expenses as well as opportunity costs. In addition, our proposed measure adjusts job accessibility by the number of destination zones each year, avoiding biases in the estimation of accessibility and facilitating its analysis over time, even with incomplete information for some spatial units.

We apply the proposed methodology to measure spatial mismatch in 2012 and 2017 for Medellín, Colombia, a developing-country city with a well-developed metro system but with persistent urban segregation, high levels of congestion, and institutional factors contributing to spatial mismatch. Medellín's transportation system had substantial expansions between 2012 and 2017, with new BRT lines, a tram in the city center, and an aerial cable route. At the same time, the system experienced high demand and congestion, with increases in the number of daily trips, usual travelers, and travel times.

Our descriptive analysis shows significant labor demand in the center and south of the city, which concentrates the city's main economic activities. We also show that travel times to work increased for all transport modes in the analyzed period (27% in private transport and 14% in public transport), even though some areas of Medellín received investment in public transport infrastructure. This pattern could indicate that these types of transport policies had limited effectiveness in mitigating congestion problems in the city. However, different potential sources that increased transportation demand in Medellín, such as increases in population or trip flows from neighboring municipalities, could have led to higher congestion even without additional transportation infrastructure.

Our estimates indicate that by 2017, job accessibility had become higher for public transport users than for private vehicle users. On average, a private transport commuter traveling to a single destination zone could access 758 jobs per USD spent on transportation, whereas a public transport user could reach 782 jobs. Additionally, accessibility declined citywide between 2012 and 2017, with private transport experiencing a steeper decrease (20%) compared to public transport (15%). This greater decline in private transport accessibility, combined with the metro system's expansion during this period, suggests that investments in public transport infrastructure may have helped mitigate spatial mismatch in Medellín.

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Appendix

A Origin-destination survey

Here, we provide details on how the Origin-Destination Survey (OD) supplies travel time data and how we use it. The survey includes comprehensive information on the origin and destination SIT zones for each trip, the departure time from the origin, and the arrival time at the destination. Additionally, it records the purpose of each trip. For our analysis, we focus only on work-related trips, thus considering only commuting times. We only observe travel times for the entire trip, so we do not have information on wait times nor separate information on travel times by different travel modes for the same trip.

The survey also provides information on transportation modes and their combinations. We classify any combination involving buses and the Metro system as public transport. Private transport includes trips using private cars, taxis, ride-sharing apps, and motorcycles. By classifying all these modes as a single private-transport mode, we assume that commuting times are similar across these categories. A more detailed description of how we use the OD to categorize trips is given in Tables A1 and A2.

Table A1. Classification of Transportation Modes into Private Transport, Public Transport, and Walking from the 2012 Origin-Destination Survey

Code OD 2012	Type	Classification
0	Walk	Walk
1-3	Bus, Microbus, Metro	Public
4	Taxi	Private
5-6	Informal, Company bus, School bus	Public
7-9	Car, Motorcycle, Bicycle	Private
50	Metroplus	Public

Notes: This Table shows how we categorize the transport modes for OD trips in 2012 into Private Transport, Public Transport, and walking. Each trip consists of multiple stages. If any stage includes a mode with code 3 (Metro system/Public), we consider that the main mode of transportation. If no such mode is found, and the first stage is walking, we take the mode observed in the second stage as the main mode. If neither of these conditions is met, we use the mode of the first stage.

Table A2. Classification of Transportation Modes into Private Transport, Public Transport, and Walking from the 2017 Origin-Destination Survey

Code OD 2017	Type	Classification
1-3	Bus, Microbus, Integrated Bus	Public
4-7	Metro (train), Metroplus, Cable, Tram	Public
8-11	Car, Motorcycle	Private
12-15	Auto rickshaw, Company bus, School bus	Public
16-18	Taxi	Private
19-20	Informal	Public
21-39	Walk (different distances)	Walk
40-41	Bicycle	Private

Notes: This Table shows how we categorize the transport modes for OD trips in 2017 into Private Transport, Public Transport, and walking. Each trip consists of multiple stages. If any stage includes a mode with a code between 4 and 7, we consider that the main mode of transportation. If no such code is found, and the first stage is walking, we take the mode observed in the second stage as the main mode. If neither of these conditions is met, we use the mode of the first stage.

B Additional figures and tables

Table B1. Public accessibility measures across distance thresholds between 2012 and 2017

Distance	Year	Accessbility	Adjusted accessibility	Count
7.0	2012	174.221	0.668	261
7.0	2017	175.237	0.573	306
8.0	2012	178.715	0.685	261
8.0	2017	179.764	0.587	306
9.0	2012	182.152	0.698	261
9.0	2017	183.281	0.599	306
10.0	2012	184.447	0.707	261
10.0	2017	185.817	0.607	306
11.0	2012	186.053	0.713	261
11.0	2017	187.615	0.613	306
12.0	2012	187.088	0.717	261
12.0	2017	188.906	0.617	306
13.0	2012	187.796	0.720	261
13.0	2017	189.810	0.620	306

Notes: This Table shows public transportation accessibility measures for 2012 and 2017 using different distance thresholds for paying a second fare in public transport. We calculate accessibility using Equation (1) and adjusted accessibility using Equation (2).

Table B2. Private accessibility measures across distance thresholds between 2012 and 2017

Distance	Year	Accessibility	Adjusted accessibility	Count
7.0	2012	161.092	0.617	261
7.0	2017	158.305	0.517	306
8.0	2012	173.779	0.666	261
8.0	2017	170.519	0.557	306
9.0	2012	184.796	0.708	261
9.0	2017	181.174	0.592	306
10.0	2012	192.799	0.739	261
10.0	2017	188.997	0.618	306
11.0	2012	197.818	0.758	261
11.0	2017	193.995	0.634	306
12.0	2012	200.751	0.769	261
12.0	2017	197.000	0.644	306
13.0	2012	202.446	0.776	261
13.0	2017	198.802	0.650	306

Notes: This Table shows private transportation accessibility measures for 2012 and 2017 using different distance thresholds for paying a second fare in public transport. We calculate accessibility using Equation (1) and adjusted accessibility using Equation (2).

Table B3. Accessibility in 2012 calculated with morning rush and entire day travel times

Mode	Time of the day	Accessibility	Adjusted accessibility
Private	Morning	186.43	0.71
Private	Entire day	186.45	0.71
Public	Morning	181.26	0.69
Public	Entire day	181.26	0.69

Notes: This Table shows accessibility and adjusted accessibility measures for public and private transportation modes in Medellín for 2012. Results are presented for the original data and the morning rush hour scenario, comparing the 5 to 9 A.M. interval to the entire day.

Table B4. Average accessibility excluding monetary travel costs

Mode	Year	Mean accessibility	Mean adjusted accessibility
Private	2012	1692.701	6.485
Private	2017	1264.710	4.133
Public	2012	583.293	2.235
Public	2017	350.004	1.144

Notes: This Table shows average accessibility with calculations considering only travel time, converted to monetary values using wages based on the equation: $A_{i,m,t} = \sum_j \frac{jobs_{j,t}}{r_{i,j,m,t} \times \bar{w}_t}, \quad r_{i,j,m,t} > 0$, where $A_{i,m,t}$ is the accessibility in zone i in year t using transport mode m (private or public). $jobs_{j,t}$ represents the number of jobs in zone j in year t. $r_{i,j,m,t}$ is the travel time (in minutes) from i to j using mode m in year t, and $\bar{w}_t$ is the average wage per minute in year t.

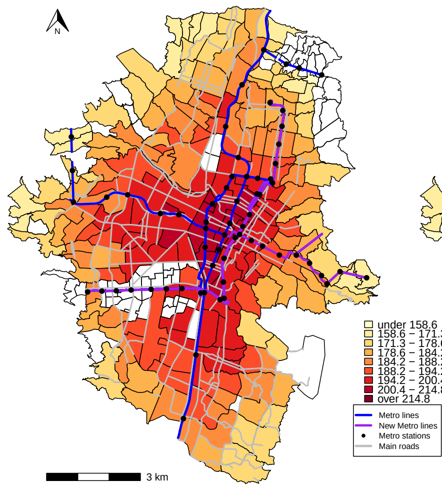
Table B5. Job accessibility by socioeconomic strata

Mode	Year	Strata	Mean accessibility	Mean adjusted accessibility	Diff adjusted 2017-2012
Private	2012	Low income	185.965	0.713	
Private	2017	Low income	170.865	0.558	-0.154
Public	2012	Low income	178.633	0.684	
Public	2017	Low income	174.575	0.571	-0.114
Private	2012	Middle income	186.357	0.714	
Private	2017	Middle income	175.691	0.574	-0.140
Public	2012	Middle income	184.660	0.708	
Public	2017	Middle income	180.330	0.589	-0.118
Private	2012	High income	189.841	0.727	
Private	2017	High income	179.312	0.586	-0.141
Public	2012	High income	193.020	0.740	
Public	2017	High income	191.209	0.625	-0.115

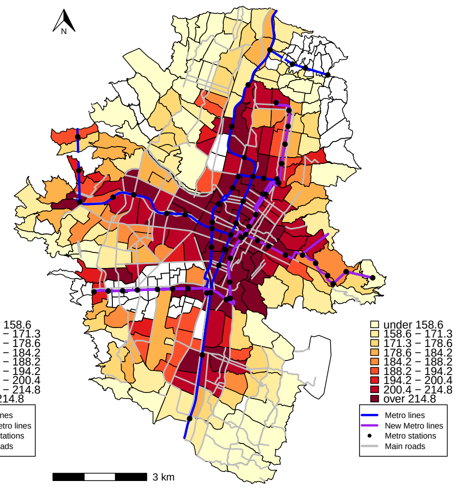
Notes: This Table presents the average accessibility and adjusted accessibility by socioeconomic strata in 2012 and 2017. The values represent the mean accessibility levels for each strata group. The last column indicates the difference in adjusted accessibility between 2017 and 2012.

Figure B1. Non-adjusted job accessibility measure

2012

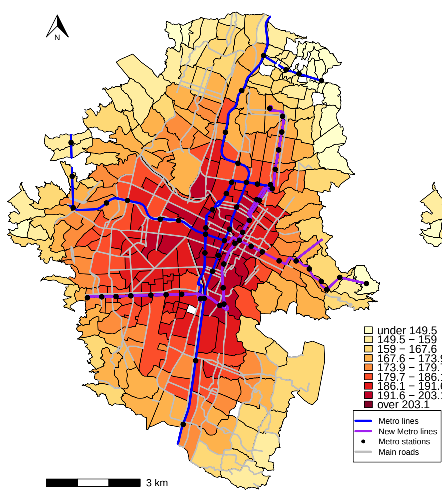


(a) Private transport

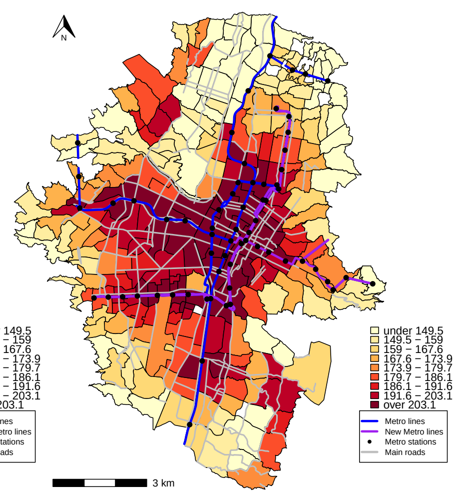


(b) Public transport

2017



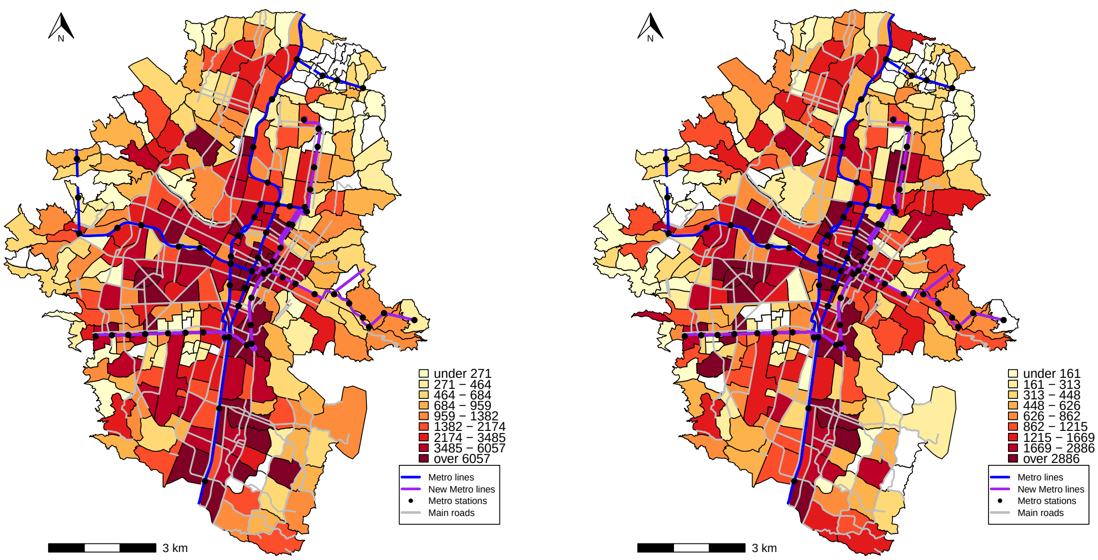
(c) Private transport



(d) Public transport

Notes: These maps show the job accessibility measure at the SIT zone level calculated using Equation (1) by year and transport mode. There were 261 SIT zones in 2012 and 306 SIT zones in 2017.

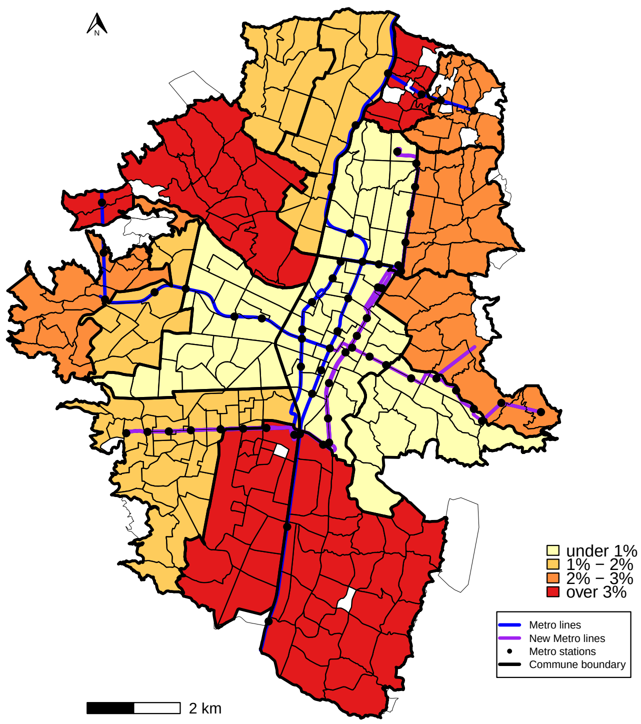
Figure B2. Spatial distribution of dependent and independent employment 2017



(a) Dependent (b) Independent

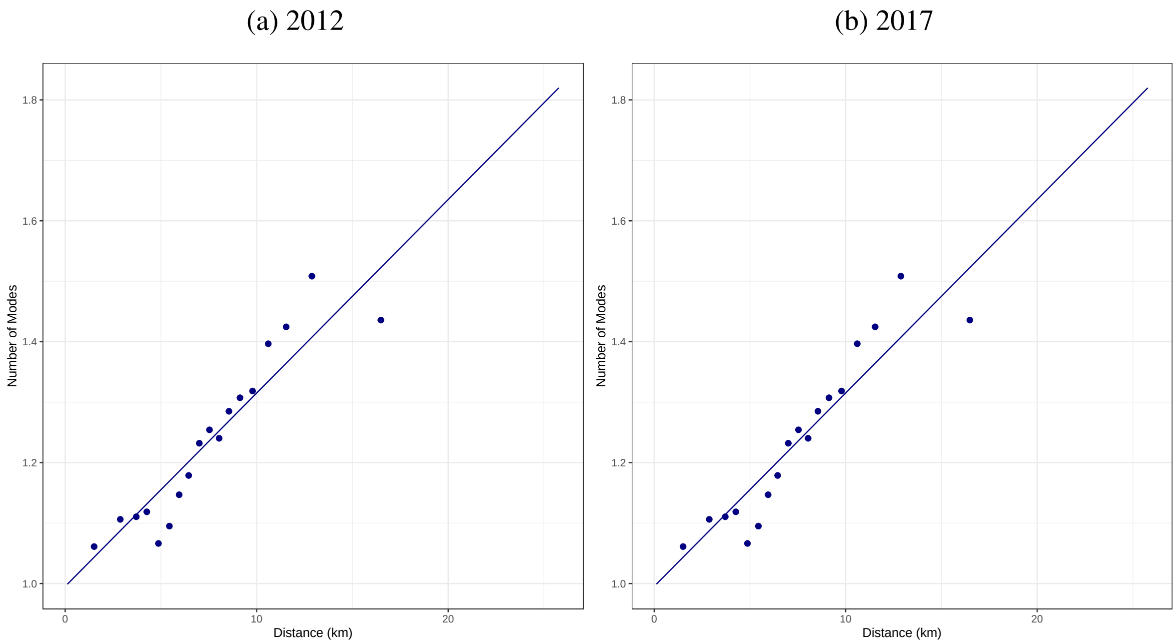
Notes: Employment density: dependent and independent employment per km^2. There were 261 SIT zones in 2012 and 306 SIT zones in 2017. Because of missing data and changes in SIT zones between years, some zones do not have assigned employment (white areas in the maps).

Figure B3. Change in population density from 2012 to 2017 (% Difference)



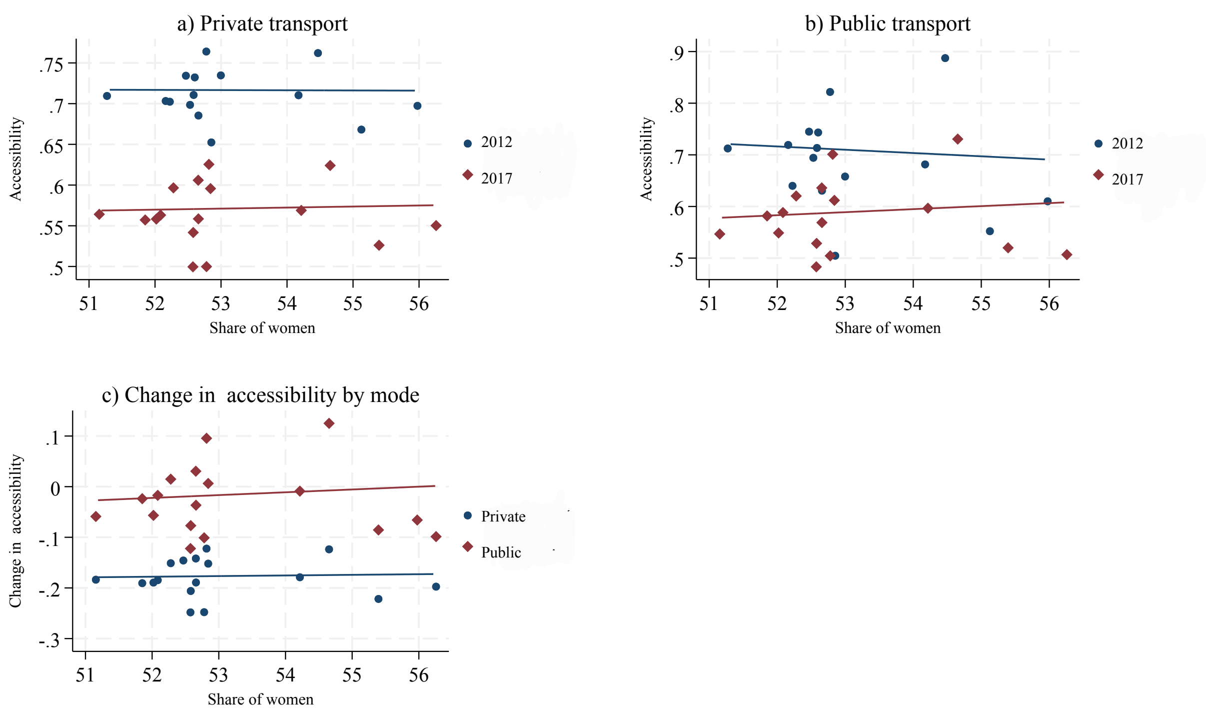
Notes: Authors' calculation with official information from DANE (2018)

Figure B4. Number of modes using public transportation and distance of commuting



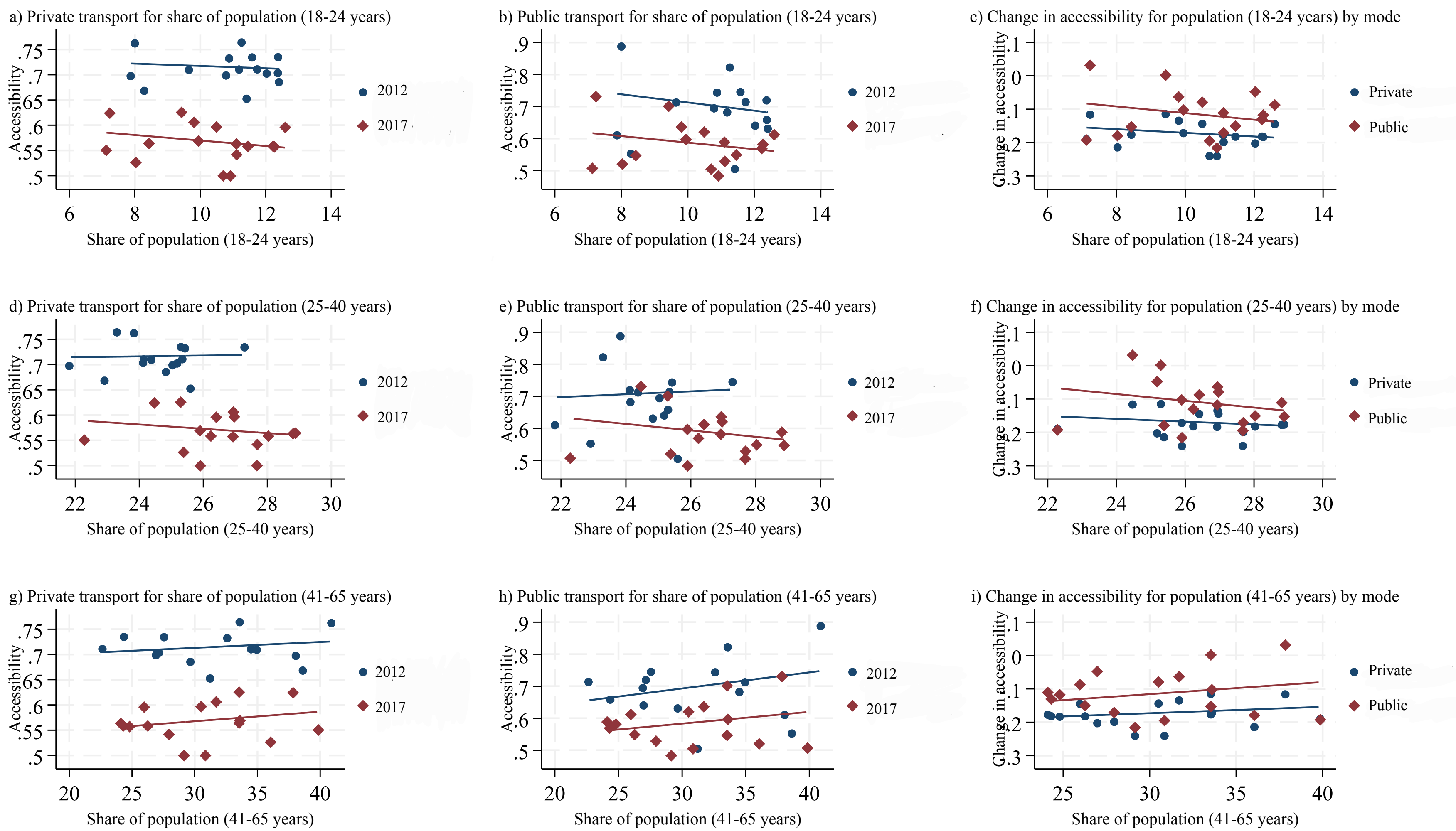
Notes: These plots show the number of rides or modes of transportation used in a trip, conditional on the use of public transportation, as a function of distance. The blue line represents the best-fit line. On the left, the figure represents data for 2012, while the right displays data for 2017. To produce the scatter plots, we used the `binsreg` command (Cattaneo et al., 2024a, 2024b) with the default settings.

Figure B5. Accessibility and share of women



Notes: These plots show the adjusted accessibility by transport mode and its change between 2012 and 2017, calculated using Equation (2), conditional on the share of women. To produce the scatter plots, we used the `binsreg` command (Cattaneo et al., 2024a, 2024b) with the default settings.

Figure B6. Accessibility and share of population of each age group



Notes: These plots show the adjusted accessibility by transport mode and its change between 2012 and 2017, calculated using Equation (2), conditional on the share of specific age intervals. To produce the scatter plots, we used the `binsreg` command (Cattaneo et al., 2024a, 2024b) with the default settings.