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 analyze accessibility to jobs through different transportation modes and the extent of spatial job mismatch at the intra-urban level in Medellín –a developing-country city– from 2012 to 2017. We propose a methodology to calculate spatial mismatch and assess its evolution over time with incomplete data, using a combination of reported travel times from origin-destination surveys and estimated travel-time data from online mapping apps. We measure job accessibility by considering employment, travel times, wages, and transportation costs. Despite investment in public transportation and transport infrastructure, spatial mismatch in Medellín increased between 2012 and 2017, and it was larger for job seekers and workers using public transportation compared to those using private transport. The results also suggest that the greatest loss in job accessibility over time was by private transport, indicating that the expansion of public transport in Medellín may have slowed down the city's spatial mismatch.

Keywords: Spatial mismatch, job accessibility, travel times, public and private transport
JEL Classification: J61, R41, R42

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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, and reduced travel times and 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 increase access to jobs, it is essential to measure the extent and effects of spatial mismatch.

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] We address the issue of incomplete data using a combination of origin-destination household surveys and travel times from online mapping apps. Our measure of spatial mismatch is a weighted employment measure at every possible destination with costs as weights. These costs include monetary transportation costs and opportunity costs for private and public transportation.

We apply our proposed methodology to measure spatial mismatch and its dynamics in Medellín (Colombia), a developing-country city. Medellín is an attractive setting to analyze spatial mismatch: developing countries such as Colombia have substantial income inequality and a prevalence of low-quality jobs, exacerbated by spatial mismatch (Duque, García, Lozano-Gracia, Quiñones, & Montoya, 2023; Oviedo, Scholl, Innao, & Pedraza, 2019; Pinto,

[1]According to Houston (2005), there are four primary methodologies for measuring spatial mismatch in the literature: analysis of the labor market impact of residential segregation, comparison of commuting times, comparison of earnings, and 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 because it relies on a measure of job proximity to approximate the spatial mismatch (Holzer, 1991; Preston & McLafferty, 1999; Wang, Wu, & Zhao, 2022).

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 used to take 34 minutes. By 2017, that time increased to 36 minutes (Medellín Cómo Vamos, 2017).

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. Our proposed measure of spatial mismatch allows comparison over time, thus enabling analyses of the spatiotemporal evolution of mismatch. 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 incidence and consequences 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, 2022; Delmelle, Nilsson, & Adu, 2021; Taylor & Bradley, 1997), wages (Dauth & Haller, 2020; Delmelle et al., 2021; Stacy & Meixell, 2020; Zenou, 2009), and job-education mismatch (Di Paolo, Matas, & Raymond, 2017; Hensen, De Vries, & Cörvers, 2009). However, there is less evidence of SMH for cities in developing countries, particularly Latin American ones. Cities in Latin American countries present an urban context characterized by a significant part of the low-income population living in peripheral areas with poor access to opportunities, especially jobs. In addition, the high degree of centralization of jobs and the lack of public transportation that serves low-income areas are barriers that vulnerable groups face when trying to reach job opportunities in a city. In these settings, spatial mismatch may exacerbate income inequality and the prevalence of unemployment and low-quality jobs (García, Badillo, & Aristizábal, 2024; Pinto et al., 2023).

For the Latin American context, Boisjoly, Moreno-Monroy, and El-Geneidy (2017) study mismatch in the São Paulo Metropolitan Region (Brazil), and Hernandez, Hansz, and Massobrio (2020) study it in Montevideo (Uruguay). These studies use a measure of cumulative job opportunities to approximate spatial mismatch, as commonly used in the literature on the spatial distribution of accessibility (Geurs & van Wee, 2004; Hansen, 1959; Wang et al., 2022). This measure of job accessibility is easy to interpret because it counts the number of jobs reachable from one region with travel time below a given threshold. However, this measure does not consider the cost of transportation, namely, monetary transportation costs and opportunity costs. In this sense, our paper aims to contribute by showing new evidence of spatial mismatch in a Latin American city, considering a measure of accessibility adjusted for transportation costs.

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

2 Methodology

Our empirical approach to measuring job accessibility considers two key variables: 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.

2.1 Job accessibility measure

To measure job accessibility, we use a weighted measure of access to employment where the weights are travel times. 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 also arises as a measure of residential commuter market access in quantitative urban models, such as Tsivanidis (2023):

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

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); $emp_{j,t}$ is the number of jobs in zone j in year t; $r_{i,j,m,t}$ is the travel time from zone i to j using mode m in year t; $\bar{w}_t$ is the average wage in t; and $c_{i,j,m,t}$ is the monetary transportation cost from i to j using transport mode m in year t .

The monetary transportation cost changes for each transportation mode. For public transport, we use the price of one metro system ticket, $fare_t$ (fares between the metro system and private buses are similar). In 2012, the fare price was 1,600 COP, or about 1.3 USD using a PPP exchange rate. In 2017, the price was 2000 COP, about 1.5 USD in PPP.[2] When the trip distance between zone i and j ($dist_{i,j}$) is over 10km, we multiply $fare_t$ by two because longer trips usually require connections with an additional ticket. We estimate private transport costs as the product of public transportation costs, $c_{i,j,pb,t}$, and the ratio between private transport and public transport expenses, δ=2.18, obtained from Colombia's 2016-2017 National Budget Survey (DANE). Because private transport costs do not discontinuously increase at 10 km, we smooth the relationship between this private cost and distance between zone i and j through a linear regression to end up with an estimated private transport cost $c_{i,j,p,t}$. In summary, the monetary transportation costs for public transport ($c_{i,j,pb,t}$) and private transport ($c_{i,j,p,t}$) are given by the following equations:

$$c_{i,j,pb,t} = \begin{cases} fare_t & \text{if } dist_{i,j} < 10 \text{ km} \\ 2 * fare_t & \text{if } dist_{i,j} \geq 10 \text{ km} \end{cases} \tag{2}$$

$$c_{i,j,pb,t} \times \delta = \beta_0 + \beta_1 dist_{i,j} + \epsilon_{i,j,pb,t} \tag{3}$$

$$c_{i,j,p,t} = \hat{\beta}_0 + \hat{\beta}_1 \times dist_{i.j} \tag{4}$$

In terms of interpretation, our accessibility measure is the number of jobs available in a ratio of 1 monetary unit from an origin. We measure the denominator in Colombian pesos, so that $A_{i.m,t}$ counts how many jobs are in a 1-peso travel cost circle centered on an origin in zone i through transport mode m in year t.[3]

[2]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.

[3]We choose to calculate accessibility in terms of jobs per Colombian peso travel cost instead of jobs per minute of travel to better reflect the differences in accessibility between public and private transport, and to be able to add monetary transport costs in a straightforward way. On a time basis, because of a higher average speed, private transportation always provides higher accessibility.

2.2 Employment

We now describe how we recover employment information at each destination from labor and origin-destination surveys. The level of employment is commonly calculated using household surveys. However, these surveys only have employment data for larger geographical units (e.g. cities or regions) and they do not provide exact information for employment at each destination. To solve this problem, we assume that employment at each destination i is proportional to the number of trips to work at this destination within each larger geographical unit $h(i)$. We then approximate the spatial distribution of employment using the following formula:

$$emp_i = empMed * \frac{W_h * empODC_{h(i)}}{\sum_h W_h * empODC_{h(i)}} * \frac{empOD_i}{\sum_{i\epsilon h} empOD_i}. \tag{5}$$

Here, emp_i is the number of jobs in the zone i, and $empMed$ is the total number of jobs in Medellín. W_h is the survey weight for the larger geographical unit h. The variables $empODC_{h(i)}$ and $empOD_i$ are the number of trips to work at h (where i belongs), and the number of trips to work to destination i, respectively.[4] In our application, the smaller geographical units i are transportation zones and the larger ones $h(i)$ are communes akin to New York boroughs. We provide additional details about this in section 3.

2.3 Travel times

We compute travel times using different methodologies for each year and 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

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

by private vehicle (cars and motorbikes).[5]

For 2012, our travel time data is incomplete because we cannot compute travel times for 2012 using the Google or Bing APIs due to the lack of historical information in them. 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, so that travel times for 2012 between a pair of zones are given by the times of 2017 adjusted for the average rate of growth in travel times between the two years per commune ($1+\Delta\overline{sr}_{m,h(i)}$), 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:

$$r_{i,j,m}(2012) = \begin{cases} r_{i,j,m}(2017) - (sr_{i,j,m}(2017) - sr_{i,j,m}(2012)) & \text{if data on } sr_{i,j,m} \text{ is available,} \\ r_{i,j,m}(2017)(1+\Delta\overline{sr}_{m,h(i)}) & \text{if data on } sr_{i,j.m} \text{ is not available.} \end{cases} \tag{6}$$

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

[5]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.

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:

$$r_{i,i,m}(t) = \frac{R_{i,outside} + R_{i,inside}}{2} * AVS_m. \tag{7}$$

2.4 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:

$$\hat{A}_{i,m} = A_{i,m,t} \times \frac{1}{n_t}. \tag{8}$$

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 1 Colombian peso 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.

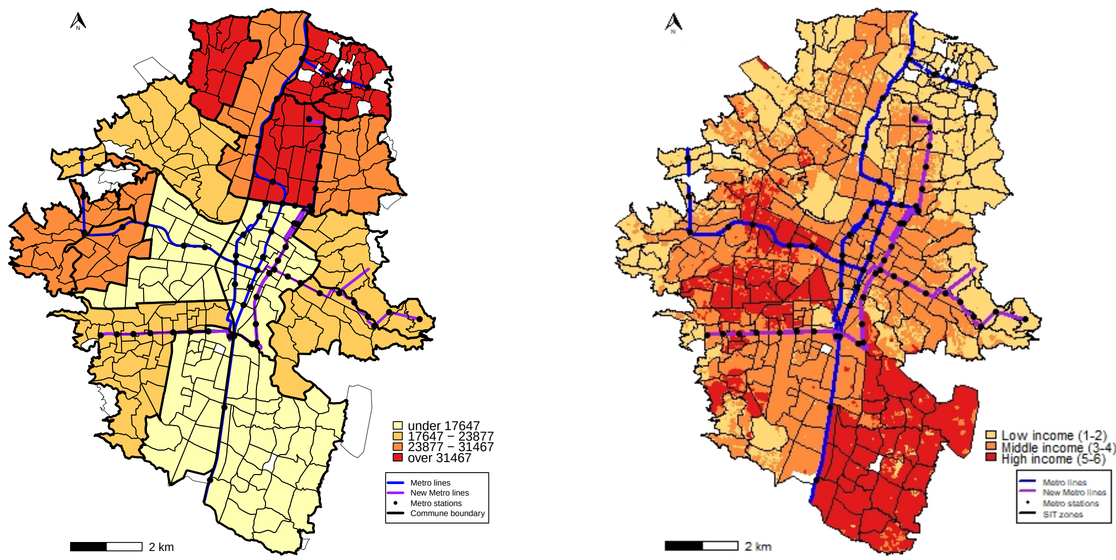
3 Study area, data, and descriptive statistics

3.1 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 Territorial Arrangement Planning of city. 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 nowadays, it transports around 1.5 million passengers daily. 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 1a). The north of the town has a low-income population and relatively well-equipped transportation infrastructure in terms of access to the Metro system (Panel 1b). 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. Income level by blocks from socioeconomic strata, which are categories defined by the Colombian government to assign social programs and subsidies (1 = very low to 6 = very high).

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

3.2 Data and descriptive statistics

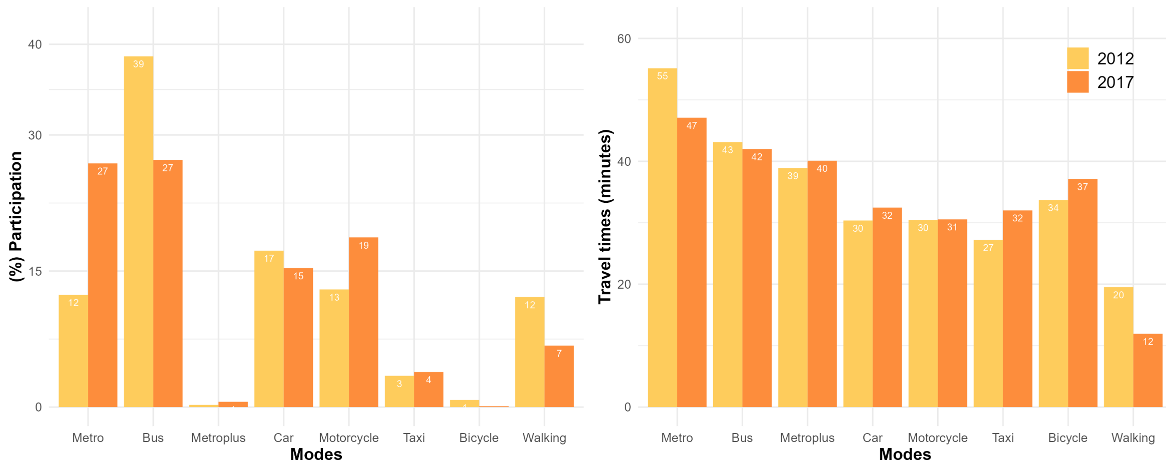
Our data comes from the Medellín Origin-Destination survey (EOD, for its acronym in Spanish, *Encuesta Origen-Destino*) for 2012 and 2017. This cross-sectional survey provides individual-level information on mobility patterns by trip purpose (work, study, home, health, and shopping), means of transportation used (metro, Metroplus - a BRT system, 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, and 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 of the private transportation modes, with reported travel time increases of 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 role of changes in mode choice in the observed measures of accessibility. Changes in the share of trips using private transportation modes such as taxis or motorcycles may have contributed to the increase in 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 is different 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. The categorization we use is very similar to the one we explained in A1 and A2. The only difference is that here we keep the modes disaggregated, but the criteria for selecting the main mode remain the same.

In terms of congestion, the Global INRIX Traffic Scorecard (INRIX, 2022) shows that Medellín is one of the most congested cities in the world. In 2017 Medellín ranked as the 18th most congested city in the world and the 3rd in Latin America, with 57 hours spent in congestion, after Sao Paulo (Brazil) and Bogotá (Colombia). In 2022 the number of hours in congestion in Medellín increased to 91h, with an average speed in the downtown area of 12 miles per hour (mph). According to González (2009) and García, Posada, and Corrales (2016) the low speeds in Medellín were the result of a saturated transportation network and transit routing converging in the downtown area.

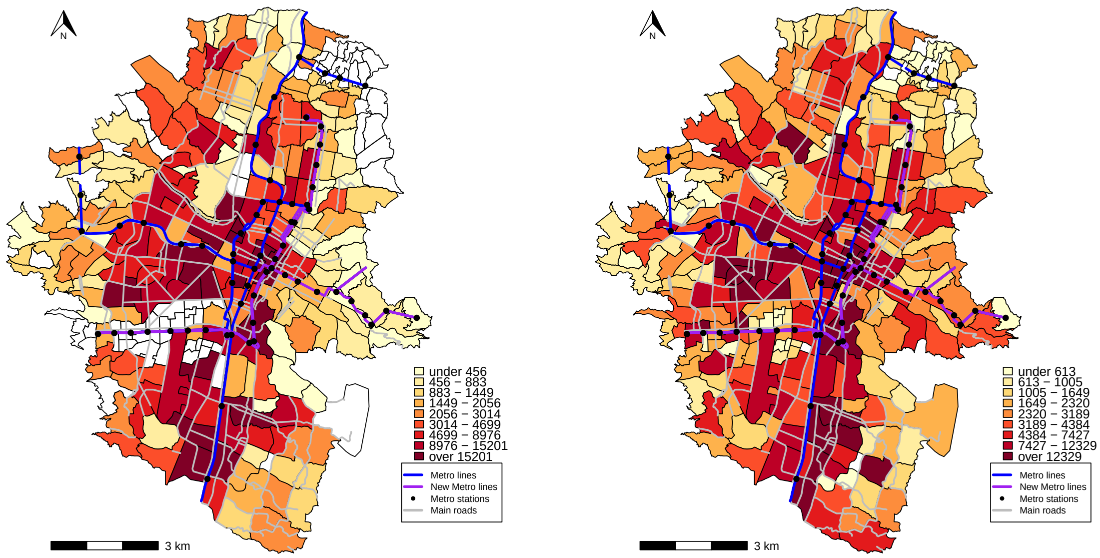
The increase in the number of trips and in the share of usual travelers show that Medellín faced a high demand for transportation in the analysis period. As a result, the transportation infrastructure may have not been able to support this demand, making mobility one of the city's major challenges (García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

Having shown the increase in the number of trips and the changes in transportation modes, we now describe where commuting trips are headed. We calculate employment at each destination from the EOD survey, using equation (5). Figure 3 shows the spatial distribution of employment calculated at the SIT zone level for 2012 and 2017.[6] We observe high employment density in areas around the Metro system. Employment increases between 2012 and 2017 along new Metro system lines in the city's east, center, and northwest. The highest employment levels concentrate in the city's south and center. These results are unsurprising since Medellín's center is the city's commercial area, whereas the southern part is industrial and contains financial and entertainment services. This polycentric structure in Medellín is consistent with the results found by Galeano (2013) and Rodríguez and García (2014), who show 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, & Parente, 2014).[7]

[6]According to the National Department of Statistics (DANE), between 2012 and 2017, employment in Medellín increased by 9.4%, from 1,665,000 workers to 1,822,000 workers.

[7]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 A2 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 employment in the city.

Figure 3. Spatial distribution of employment



(a) 2012 (b) 2017

Notes: These maps show the spatial distribution of employment for 2012 and 2017, Employment density: employment per km^2. Because of missing data and changes in SIT zones between years, there are some zones without assigned employment (white areas in the maps). There are 261 SIT zones in 2012 and 306 SIT zones in 2017.

We use different approaches depending on the year analyzed to compute travel times by transportation mode. For 2012 we follow Equation (6) 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. In terms of average travel times and the differences between years, Table 1 shows that both computed and reported travel times increased for all transport modes between 2012 and 2017. With computed travel times, we observe that for 2012 it took a person around 20 minutes to get to work by private transport, and 48 minutes to do so by public transport. For 2017 these commuting times 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)

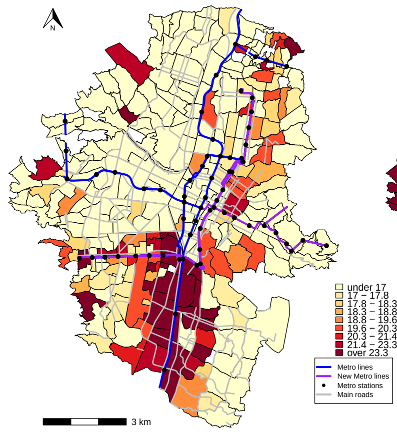
Transport mode	Mean 2012	Mean 2017	Diff means 2017-2012	% Diff means 2017-2012
A. Computed travel times				
Private	19.50	24.87	5.37	27.53%
Public	48.32	55.08	6.76	13.99%
B. Reported travel times				
Private	25.06	30.73	5.67	22.62%
Public	39.14	47.94	8.80	22.48%

Notes: Panel A shows computed travel times calculated using Equation (6). 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 EDO survey.

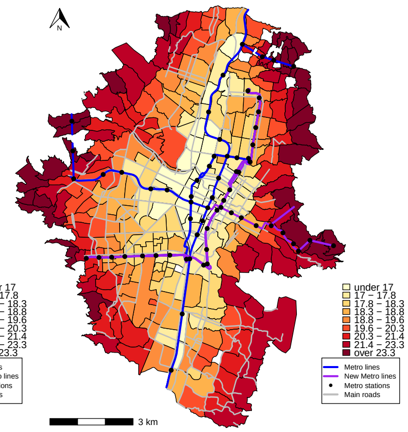
Figure 4 shows computed average travel times by SIT zone calculated at the origin level. This figure shows that for private transport travel times tend to be higher in the outskirts of the city, and for public transport, lower travel times are strongly associated with the presence of Metro lines.

Figure 4. Spatial distribution of computed average travel times at the origin by transport mode

Private transport

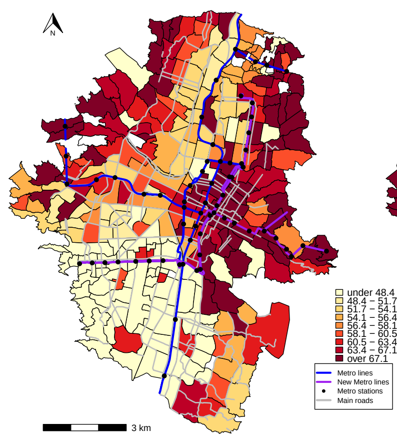


(a) 2012

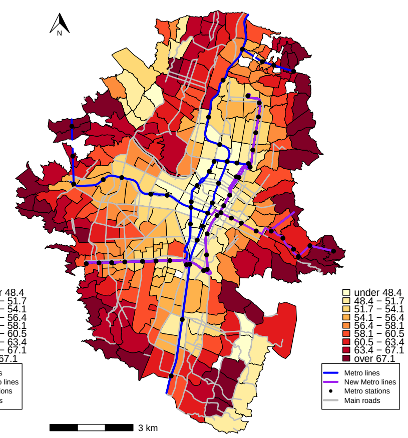


(b) 2017

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.

4 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 present all of our results in terms of the accessibility measure, which is inversely related to mismatch.

4.1 Job accessibility by years and transportation modes

Table 2 shows average job accessibility measures by transportation mode and year. To account for sampling variation in our employment measures, we obtain confidence intervals for the mean accessibility measures via bootstrapping.[8] With the non-adjusted measure, we observe that job accessibility using private transportation is higher than the one by public transport. In 2017, travelers could find, on average, 294 jobs in a radius of 1 Colombian peso by private transport, while by public transport there were 290 jobs in the same radius. In U.S. dollar figures, using the PPP exchange rate, this means that in a radius of 1 USD an individual could reach about 390,000 jobs in private transport and 385,000 jobs by public transport. A comparison of the non-adjusted measure across years shows that job accessibility increased in Medellín from 2012 to 2017, and that the increase in job accessibility was grater for public transportation.

However, as mentioned above, unadjusted job accessibility may increase over time just because of the 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 0.959 jobs (1270 jobs) in private transport and 0.949 jobs (1260 jobs) by public transport. Nevertheless, the comparison across years shows that job accessibility decreased in Medellín between 2012 and 2017. The difference in job accessibility between 2012 and 2017 is negative and statistically significant, and the drop

[8]Specifically, we first draw an employment total for the entire city accounting for the sampling error in Medellín's labor survey. Then, we draw shares of employment by SIT zone using the distribution of employment from the EOD survey.

was greater in private transport than public transport, with decreases in job accessibility of 14% and 12%, respectively.

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	291.63	1.117	293.63	0.959	-0.161	-14.41%
		[1.100, 1.136]		[0.947, 0.973]		[-15.94%, - 12.44%]
Public	280.43	1.074	290.39	0.949	-0.125	-11.64%
		[1.106, 1.093]		[0.934, 0.961]		[-13.70%, - 10.09%]

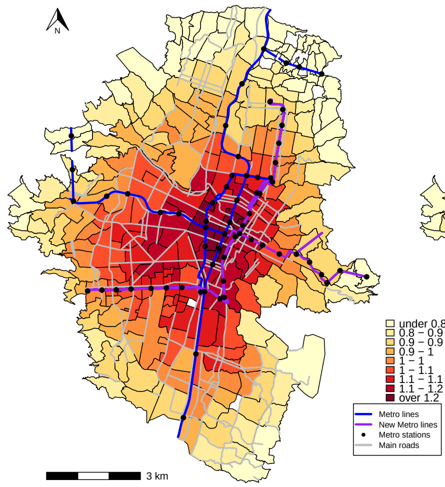
Notes: This table shows average job accessibility measures calculated using Equation (1) for the non-adjusted measure and Equation (8) for the adjusted measure. The number of zones is 261 SIT zones in 2012 and 306 SIT zones in 2017. Values in brackets represent 95% confidence intervals calculated by resampling employment at the SIT zone level using a paired bootstrap with 1000 repetitions.

Figure 5 shows the spatial distribution of adjusted job accessibility[9]. We observe that there is higher job accessibility (and lower spatial mismatch) in the center and south of the city where employment is 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 to be 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.

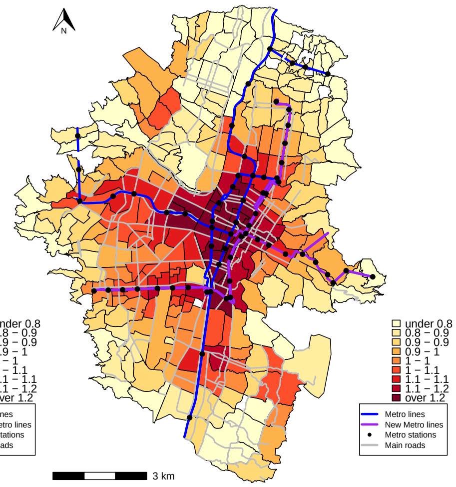
[9]We also show the distribution of unadjusted job accessibility in figure A1in the appendix

Figure 5. Adjusted job accessibility

2012

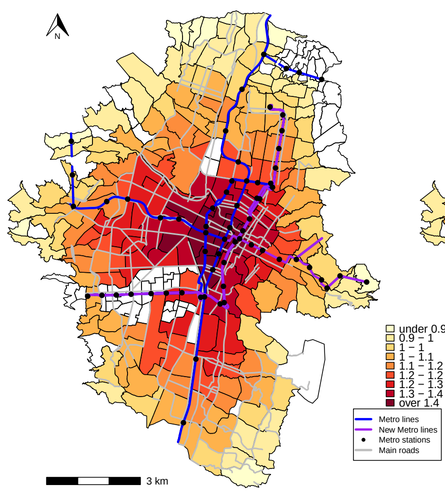


(a) Private transport

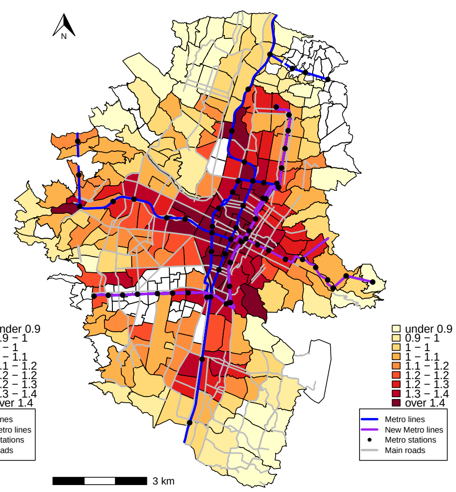


(b) Public transport

2017



(c) Private transport



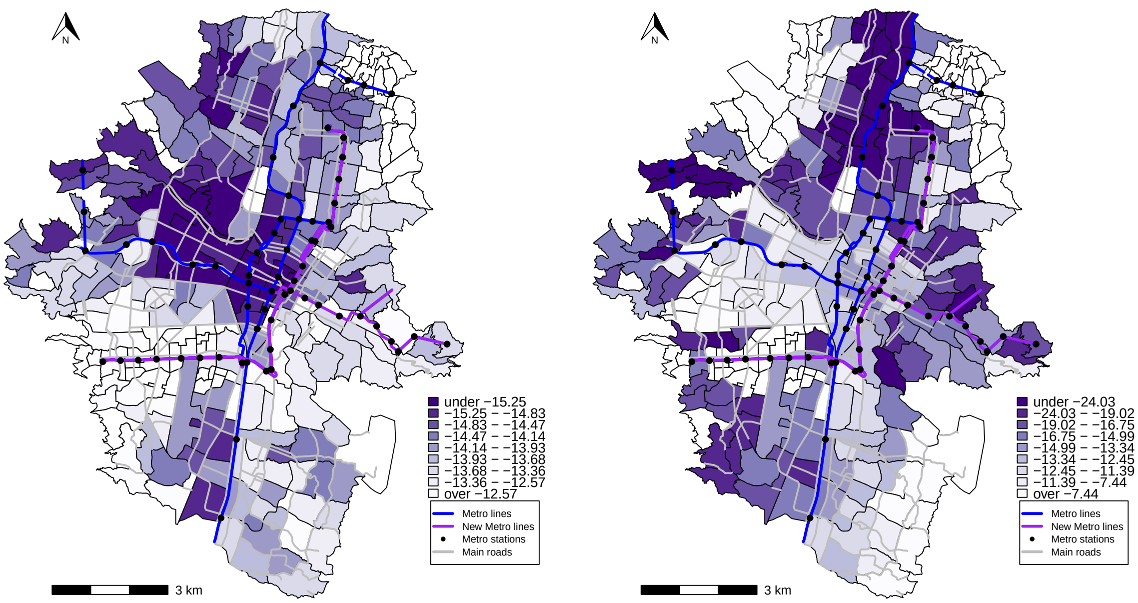
(d) Public transport

Notes: These maps show the adjusted job accessibility measure at the SIT zone level calculated using Equation (8) by year and transport mode. There are 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 from 2012 to 2017 everywhere. Employment from 2012 to 2017 increased 9.4%, but the increase in travel times offset it and led to lower accessibility in 2017. We also observe a lack of direct evidence of an increase in the accessibility of areas close to the new metro lines. Although we do not engage in a counterfactual analysis, this lack of an increase implies that at most, the new metro lines may have slowed down the city-wide decrease in accessibility. Moreover, Panel (b) shows that public transport accessibility decreased faster than private accessibility.

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 changing accessibility even in absence of changes in travel time. Appendix figure A3 shows that there is little spatial correlation between changes in accessibility and changes in populations density. Moreover, density increased throughout the city from 2012 to 2017. If higher density were associated to a higher number of jobs and travel times had remained constant, we would expect an increase in accessibility. Instead, accessibility decreased in all areas because of the higher travel times.

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.

Another result worthy of attention concerns the evolution of the accessibility gaps between private and public transportation for both years. In 2012 the gap was 0.043, while in 2017 the gap was 0.010 (see Table 2). Even though overall accessibility using any transportation mode decreased, the difference in accessibility using private transport relative to public went down. This gap decrease supports the hypothesis of an effect of public transport on slowing down the increasing spatial mismatch in the city.

5 Conclusions

In this paper, we analyzed the spatial connectivity to jobs at the intra-urban level through different modes of transport. We specifically studied the case of Medellín, Colombia, where there has been an effort to enhance public transport infrastructure. From 2012 to 2017, the metro system expanded its operations with new BRT lines, a new tram in the city's center, and a new aerial cable route.

We propose an alternative methodology to calculate spatial mismatch at the intra-urban level, considering information on employment, travel times, wages, and transportation costs.By including the monetary transport costs,this methodology allows for a better assessment of the differences in job accessibility between modes of transportation. In addition, it enables analysis of the evolution over time of spatial mismatch when there is incomplete information for some spatial units.

The results show that in Medellín, for 2012 and 2017, accessibility to jobs was higher by using private vehicles than by using public transportation, and there was a decrease in accessibility across years for both transport modes. Although there was an overall drop in access to jobs, the greatest loss of accessibility was by private transportation, which could suggest that the effort to improve public transport infrastructure in the city helped mitigate the spatial mismatch.

We argue that public transport policies that focus solely on system expansion are not sufficient to reduce urban spatial mismatch. Medellín and other cities in developing countries are characterized by high levels of congestion and difficulties in expanding public transport routes, so urban planners and policymakers should consider alternative measures to increase urban accessibility. One policy could be an increased support for alternative use of public and non-motorized transport, improving the necessary infrastructure for articulating it to the already existing public infrastructure. Another policy could be a price-based mechanism such as congestion charging. These types of policies have been implemented in other cities, such as London, Singapore, Stockholm and Chicago, and have shown positive effects on accessibility (Börjesson, Eliasson, & Hamilton, 2016; Börjesson, Eliasson, Hugosson, & Brundell-Freij, 2012; Eliasson, 2008; Goh, 2002; Litman, 2005).

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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 clearer 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.

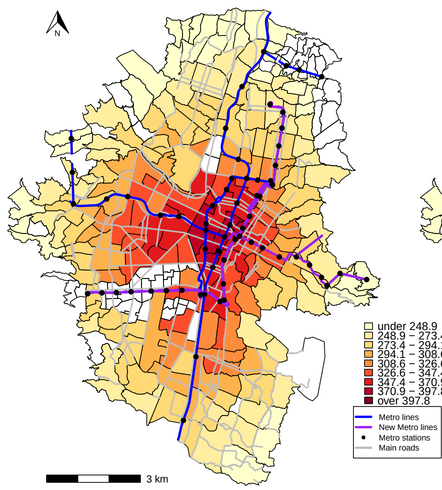
Table A2: Classification of Transportation Modes into Private Transport, Public Transport, and Walking from the 2017 Origin-Destination Survey

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

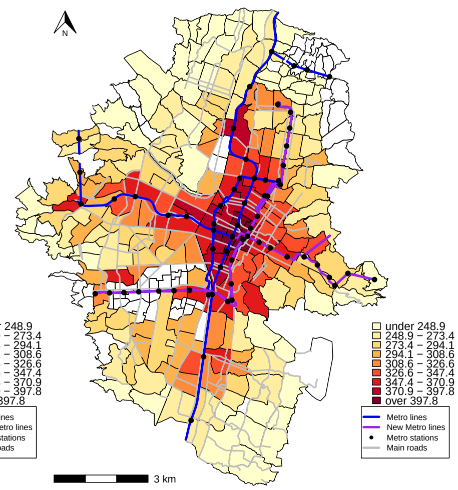
Notes: This table shows how we categorize the transport modes for OD trips in 2017 into Private Transport, Public Transport, and Walking. Each trip consists of multiple stages. If any stage includes a mode with a code between 4 and 7, we consider that the main mode of transportation. If no such code 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.

Figure A1. Non-adjusted job accessibility measure

<u>2012</u>

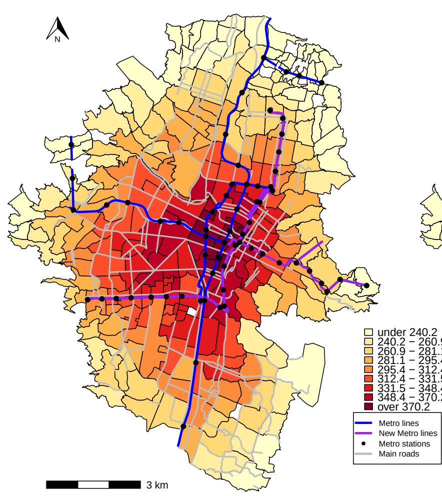


(a) Private transport

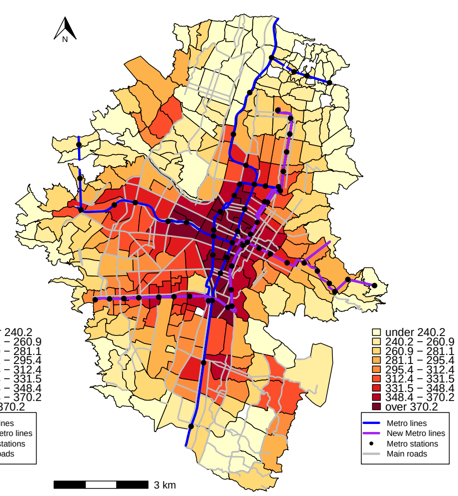


(b) Public transport

<u>2017</u>



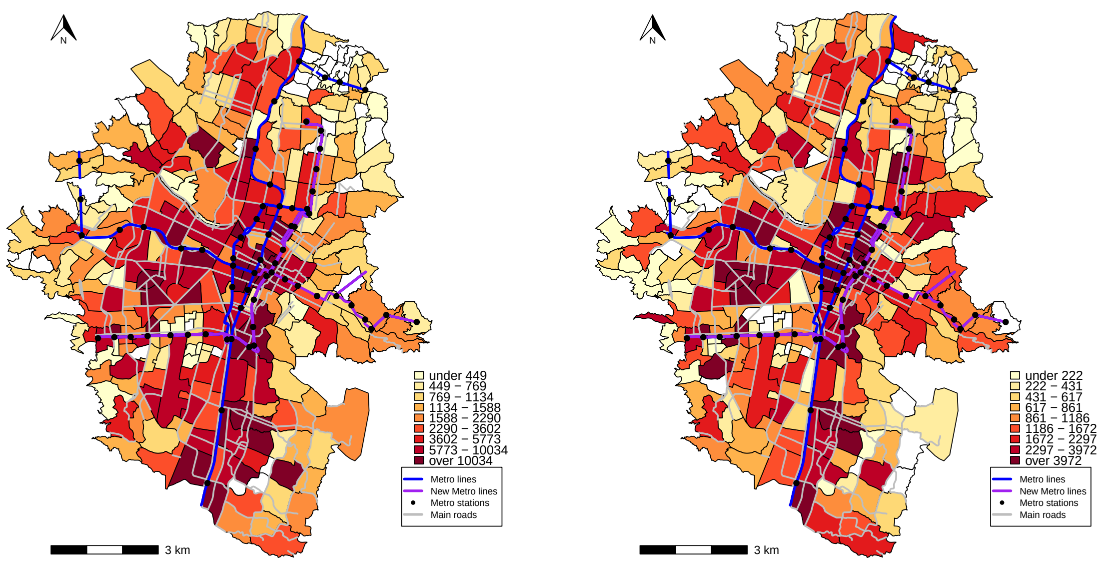
(c) Private transport



(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 are 261 SIT zones in 2012 and 306 SIT zones in 2017.

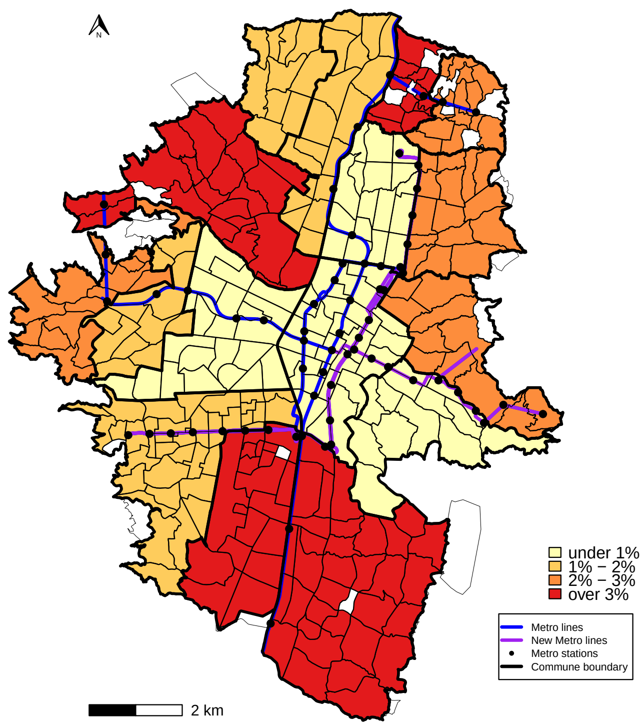
Figure A2. Spatial distribution of dependent and independent employment 2017



(a) Dependent (b) Independent

Notes: Employment density: Dependent and Independent employment per km^2. There are 261 SIT zones in 2012 and 306 SIT zones in 2017. Because of missing data and changes in SIT zones between years, there are some zones without assigned employment (white areas in the maps)

Figure A3. Change in population density from 2012 to 2017 (% Difference)



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