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 has increased, and it is considerably larger for job seekers and workers using public transportation compared to those using private transport.

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 may lead to poor labor market outcomes in cities, such as reduced labor earnings, a low employment rate, and low-quality jobs. In contrast, better job accessibility reduces travel times and improves local labor market conditions. Getting a position closer to home can be seen as welfare-increasing (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). To address spatial mismatch and to design a public policy that increases job access, it is essential to have proper measures of job accessibility.

We propose a methodology to calculate spatial job mismatch at the intra-urban level and apply it to Medellín, Colombia, a developing-country city. We show how to calculate spatial mismatch with incomplete data using a combination of origin-destination household surveys and travel times from online mapping apps. We find evidence of decreasing accessibility despite an increasing number of jobs and investment in new transportation infrastructure. We also find that workers who can commute by private transport have greater job accessibility.

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 (Halden, 2002; Heilmann, 2014). Compared to the capital city of Bogotá, Medellín has a well-developed metro system. The city has made significant in public transport and infrastructure investments over the last decade but still has substantial poverty and urban segregation by income. Travel times in the city have been increasing for all transportation modes. In 2012, an average trip in Medellín used to take 33 minutes, while in 2017, that time increased to 36 minutes (Medellín Cómo Vamos, 2017).

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. We measure spatial mismatch for private and public transportation. Our accessibility measure is an inverse measure of spatial mismatch since low accessibility implies more disconnection from jobs.

We contribute to several branches of literature. First, we contribute to articles measuring the incidence and consequences of spatial mismatch (henceforth abbreviated as SM) (Gobillon et al., 2007; Kain, 1968). This literature has associated SM with poor labor market outcomes and welfare losses. It has also pointed out mechanisms that lead to SM, such as high commuting costs, inefficient job search, territorial discrimination, and low productivity. There is evidence of SM in developed countries leading to higher unemployment rates and wage differentials (Stacy, Meixell, & Lei, 2019; Taylor & Bradley, 1997). There is also evidence of an association between SM and job-education mismatch (Di Paolo, Matas, & Raymond, 2017; Hensen, De Vries, & Cörvers, 2009). Some papers find that wages must compensate for differentials in the labor market. Jobs that are further away from residential centers hire fewer employees with long commutes, and commuters demand higher salaries for longer commutes (Dauth & Haller, 2019; Zenou, 2009).

For developing countries, the literature has focused on measuring the costs, consequences of congestion and the effects of transport infrastructure on SM. Scholl, Mitnik, Oviedo, and Yañez-Pagans (2018) evaluate the impact of a bus rapid transit system (BRT) on employment in Lima, Peru. They find evidence of large and significant effects on hours worked, employment, and monthly labor income. Martinez, Sanchez, and Yáñez-Pagans (2018) evaluate the impact of aerial cable cars in La Paz, Bolivia. They obtain very similar results than in the Peruvian case. Moreno-Monroy and Ramos (2015) check the effect of public transport on informality in Sao Paulo. They find that informality rates decreased faster on average in the areas that received public transport infrastructure relative to those which did not. Scholl et al. (2018) evaluate the BRT system's effect on job opportunities in Lima, Perú. For Colombia, Akbar and Duranton (2017) study the congestion cost in Bogotá and estimate its associated deadweight loss. Guzman, Oviedo, and Cardona (2018) show how lack of coordination between public transportation expansion and its distribution across space leads to unequal access to employment.

We contribute to this literature by providing a way to calculate spatial mismatch over time with incomplete data, thus enabling analyses of the evolution of spatial mismatch in other developing country settings. Specifically, we show how to combine origin-destination surveys with travel-time and employment-survey data to calculate spatial mismatch in the cross-section. We also propose an adjusted accessibility measure that we can compare over time. Other solutions to data limitations have relied on alternative sources such as nighttime luminosity (Mitnik, Yañez-Pagans, & Sanchez, 2018). We also contribute by providing evidence on spatial mismatch at the intra-urban level, as opposed to other papers measuring mismatch across larger geographical areas (Di Paolo et al., 2017).

The rest of this paper proceeds as follows: Section 2 describes our procedures to capture employment and spat 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 at 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 level and travel times. In addition, we propose an adjustment to the job accessibility measure, which allows for comparing 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:

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

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). When the trip distance is over 10km, we multiply $fare_t$ by two because longer trips usually require connections with an additional ticket. We estimate public transport costs as the product of public transportation costs $c_{i,j,pb,t}$ and the ratio between public transport and public transport expenses, δ, obtained from a Consumer Expenditure Survey. Because private transport costs do not discontinuously increase at 10 km, we smooth the relationship between this private cost and distance through linear regression to end up with an estimated private transport cost $c_{i,j,p,t}$.

$$\begin{aligned} c_{i,j,pb,t} &= \quad fare_t \;\; \text{if distance}(i,j) < 10km \\ &= 2 * fare_t \;\; \text{if distance}(i,j) \geq 10km \end{aligned} \tag{2}$$

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

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

Our accessibility measure is the number of jobs available in a ratio of 1 monetary unit from an origin. We measure the denominator in pesos, so $A_{i.m,t}$ 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.

2.2 Employment

We now describe how we recover employment information at each destination from labor and origin-destination surveys. The labor survey we use in this paper –as is the case with many developing country labor surveys– does not provide exact information for employment at each destination. We only have employment data for larger geographical units.

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 the city. The weight W_h is the survey weight for the larger geographical unit h. The employment 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.[1] In our

[1] We are counting just one trip to work per person.

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 these 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 by private vehicle (cars and motorbikes).[2]

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:

[2] 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.

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

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 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:

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

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 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

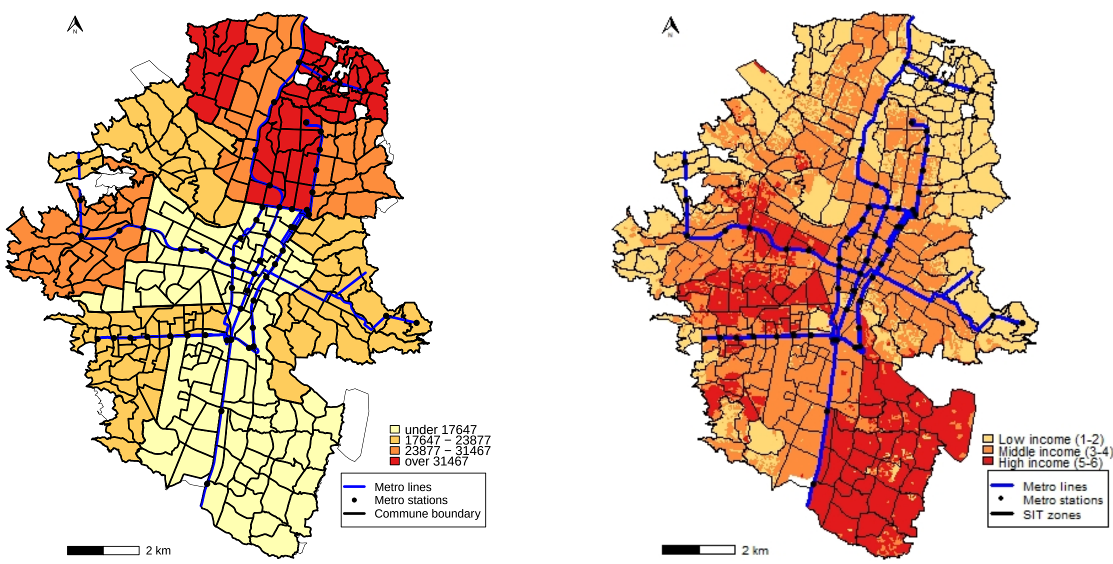
3.1 Study area: Medellín

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 de Transporte Integrado*). 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 (Área Metropolitana Valle de Aburrá, 2017).

An 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 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 communes (people per km^2) (b) Income distribution by blocks

Notes: Income level by blocks from socioeconomic strata, which are six categories defined by the Colombian government to establish subsidies of social programs (1 = very low to 6 = very high).

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

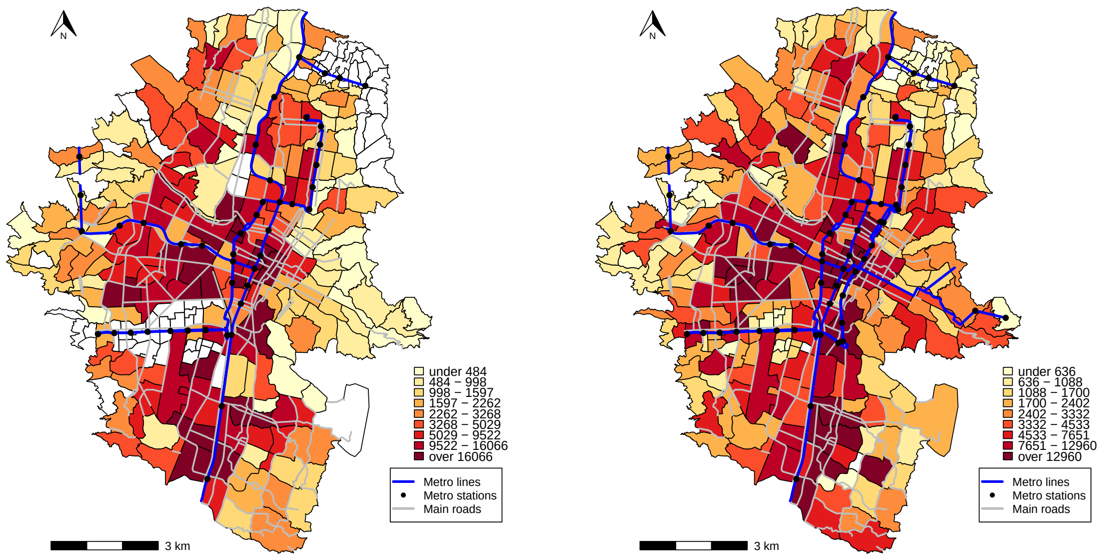
3.2 Data and descriptive statistics

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, bus, car, taxi, bicycle, motorbike, and walking), travel times, trips, and demographics. The information in the EOD survey is representative at the SIT zone level, and there were 250 SIT zones in 2012 and 310 SIT zones in 2017. The average SIT zone has an area of 0.33 km^2.

We calculate employment at each destination from the EOD survey, as defined in equation (5). Figure 2 shows the spatial distribution of employment calculated at the SIT zone level for 2012 and 2017.[3] We observe high employment density in areas around the Metro system. The main employment changes between years appear 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.

[3]According to the National Department of Statistics (DANE), between 2012 and 2017, employment in Medellín increased by 8%, $1,665,000$ workers to $1,799,000$ workers.

Figure 2. Spatial distribution of employment



(a) 2012 (b) 2017

Notes: 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 250 SIT zones in 2012 and 310 SIT zones in 2017.

We used different approaches depending on the year analyzed to compute travel times variables 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 transport and private transport using 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 have increased for all transport modes between 2012 and 2017. With calculated travel times, we observe that for 2012 in private and public transport, it takes a person around 20 and 52 minutes to get to work, respectively, for 2017 these commuting times increase to 25 and 55 minutes, respectively. These results imply an increase of 23% in travel times in private transport and 7% in public transport, which may be associated with increases in congestion levels in the city (Restrepo, 2012).

Table 1: Computed and Reported travel times (minutes)

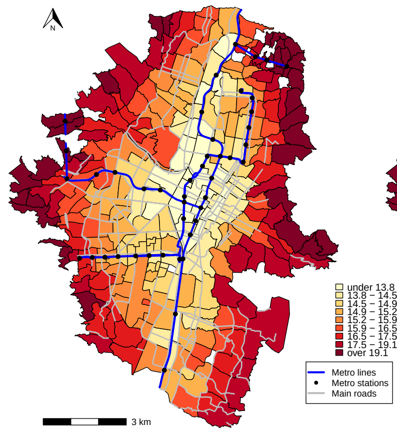
Transport mode	Mean 2012	Mean 2017	Diff means 2017-2012	% Diff means 2017-2012
A. Computed travel times				
Private	20.20	24.87	5.28	23.1%
Public	51.64	55.08	3.45	6.65%
B. Reported travel times				
Private	24.86	30.14	5.29	21.26%
Public	39.14	45.44	6.30	16.08%

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 takes into account all the possible trips in the origin-destination matrix, while reported travel times only considers the trips that are actually made.

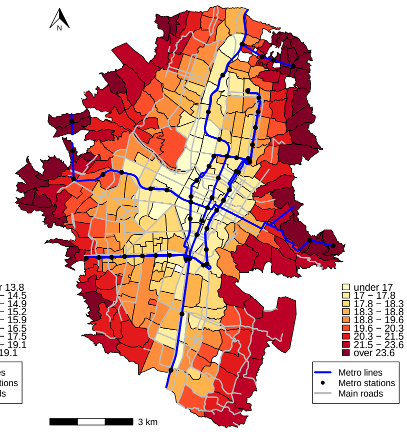
Figure 3 shows the spatial distribution of computed average travel times, which are calculated at the origin level showing that for private transport the travel times tend to be higher in the Outskirts of the city, and for public transport, we can see that the lower travel times are strongly associated with the Metro lines.

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

Private transport

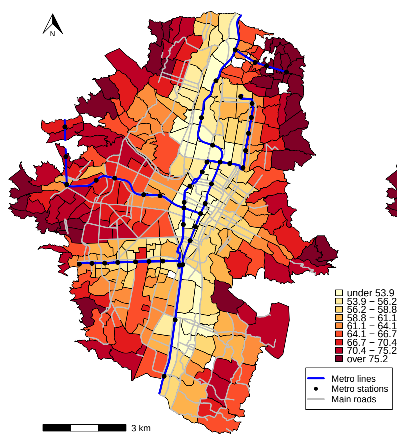


(a) 2012

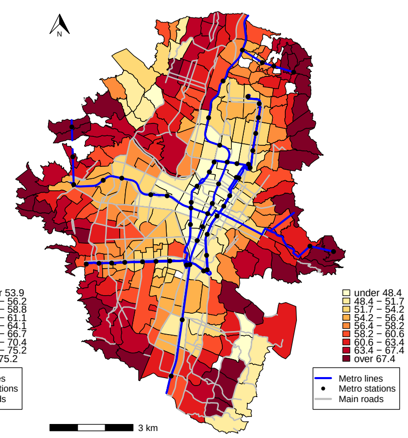


(b) 2017

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.

4 Results

This section presents our results for spatial mismatch in Medellín for 2012 and 2017 and its evolution over time. Our empirical assumes that there is always a spatial mismatch. This assumption is reasonable if we consider the mechanisms presented by Gobillon et al. (2007). Our accessibility measure is inversely related to mismatch since accessibility means faster transportation or more jobs nearby.

4.1 Job accessibility by years and transportation modes

Table 2 shows the means of job accessibility measure in its versions non-adjusted and adjusted, by transport mode and year. We observe that job accessibility using private vehicles is higher than the one by public transport. In 2017, travelers could find, on average, 307 jobs in a radius of 1 peso by private transport, while by public transport there were 303 jobs in a radius of 1 peso, and the difference is statistically significant. The comparison by years shows that job accessibility has decreased substantially in Medellín from 2012 to 2017, where the accessibility for private and public transport has decreased around 16%.

Figure 4 shows the spatial distribution of non-adjusted job accessibility measure. We observe that there is higher job accessibility (and lower spatial mismatch) in the center and south of city where employment is concentrated and public transport present higher incidence. By transport mode, we note that private transport offers higher job accessibility, being this accessibility more decentralized than public transport. When we compared job accessibility by years it is noted that there is not a big difference with 2017 in terms of distribution. However, in Panel (b), accessibility seems 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 significantly impact the distribution of accessibility.

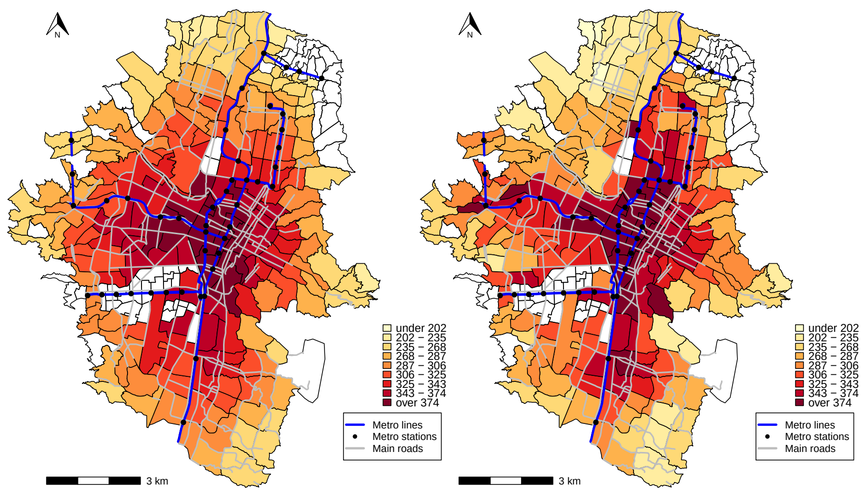
Table 2: Job accessibility measure

Transport mode	Mean 2012	Mean adjusted 2012	Mean 2017	Mean adjusted 2017	Diff adjusted	%Diff adjusted
Private	310.32	1.19	307.47	1.00	-0.19	-15.77%
Public	305.01	1.17	303.72	0.99	-0.18	-15.37%
Diff	5.31	0.02	3.75	0.01		

Notes: This table shows the means of job accessibility measure calculated using Equation (1) for non-adjusted measure and Equation (8) for adjusted measure, respectively.

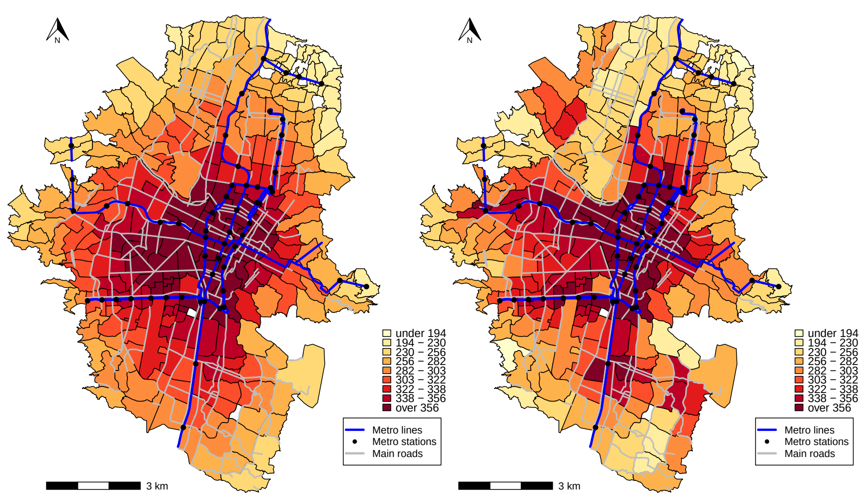
Figure 4. Non-adjusted job accessibility measure

2012



(a) Private transport (b) Public transport

2017

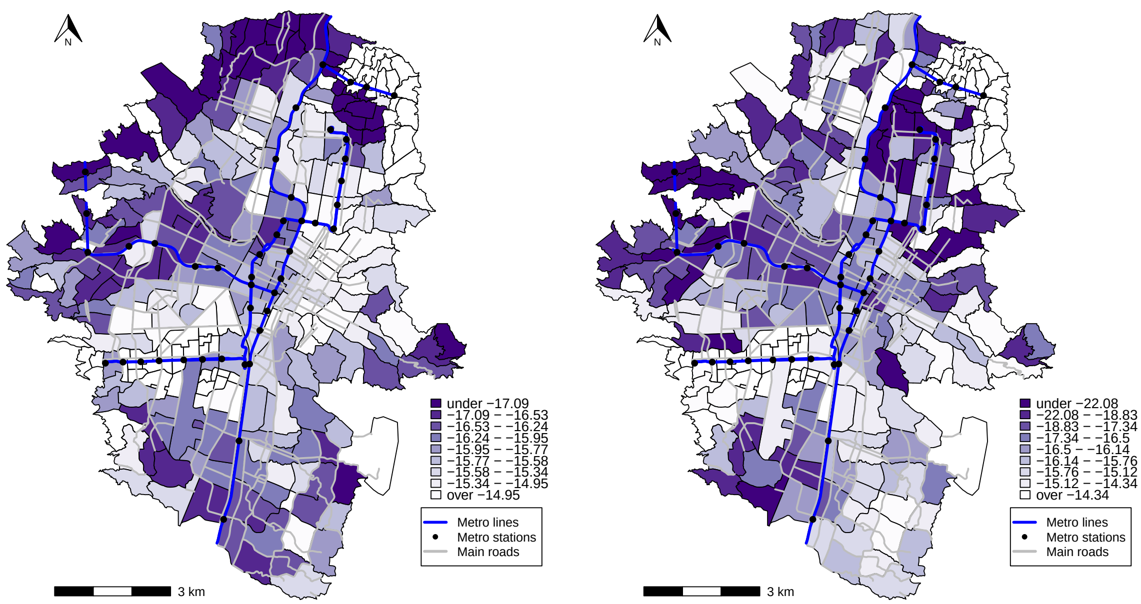


(c) Private transport (d) Public transport

Notes: These maps show the job accessibility measure calculated using Equation (1) by year and transport mode.

To compare both measures for 2012 and 2017, we analyze the evolution of the adjusted job accessibility measure. Figure 5 shows that average adjusted accessibility has decreased from 2012 to 2017. It is lower in 2017 for all the zones where we have information. Employment from 2012 to 2017 increased 8%, 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 the new metro lines could at most have slowed down the city-wide decrease in accessibility. Moreover, Panel (b) shows that public transport accessibility decreases faster than private accessibility.

Figure 5. (%) Difference of adjusted job accessibility measure 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 measure 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 5.31, while in

2017, the gap was 3.75 (see Table 2). Even though overall accessibility using any transportation mode decreased, the difference in accessibility using public transport relative to private 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.

Our analysis shows that in 2012 and 2017, accessibility to jobs was higher by using private vehicles than by using public transportation. The gap between modes was reduced, by a small proportion, in 2017. This evidence is informative for environmental policies since it provides a rationale for private vehicle use –increased job access– that could otherwise be deemed excessive. Spatial mismatch between 2012 and 2017 increased indistinctly, by a faster proportion for public transport. The more significant employment density did not offset this rise in the spatial mismatch.

We argue that public transport and road infrastructure policies have not reduced spatial mismatch in the city, although they may have slowed down its worsening. The increasing traffic, larger waiting times, and the impossibility of expanding public transportation routes may have kept accessibility stagnant. Therefore, it could be helpful to approach this problem from a different perspective. Policies focused on telecommuting could be brought into play to reduce commuting costs. Urban planners and policymakers should consider that having access to a private vehicle in Medellín is currently more efficient in terms of job accessibility and that public transport policies alone have not led to a reduction of city-wide spatial mismatch.

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