Better or Worse Job Accessibility? Understanding Changes in Spatial Mismatch at the Intra-urban Level in Medellín

David Bernal[*] Gustavo A. García [†] Jorge Pérez Pérez[‡]

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Abstract

We analyze accessibility to jobs through different transportation modes and the extent of job spatial mismatch at the intra-urban level in a developing country city. We propose a methodology to calculate spatial mismatch and assess its evolution over time in presence of incomplete data, using a combination of reported travel times from origin-destination surveys and estimated travel time data from mapping applications. We use data from Medellín, Colombia, from 2012 to 2017, to measure accessibility using employment weighted by travel times. We find that despite the continuous 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 transport compared to those using private transport.

Keywords: Spatial Mismatch, Accessibility, Travel times
JEL Classification: J10, J70, R10, R12, R42

[*]Universidad EAFIT, Medellín, Colombia. E-mail: vdbernalp@eafit.edu.co
[†]Universidad EAFIT, Medellín, Colombia. E-mail: ggarci24@eafit.edu.co
[‡]Banco de México, Mexico City, Mexico. E-mail: jorgerpp@banxico.org.mx

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1 Introduction

Spatial disconnection from jobs in cities may lead to negative labor market outcomes, such as reduced labor earnings, a low employment rate, or low-quality jobs. The negative relationship between spatial disconnection from jobs and positive labor market outcomes is referred to as the Spatial Mismatch Hypothesis (SMH) (Gobillon, Selod, & Zenou, 2007). Better job accessibility nor only reduces travel times, but also improves local labor market conditions. Getting a job closer to home can be seen welfare-increasing (Ong & Blumenberg, 1998). The measurement of job accessibility is important for the design of public policy to increase job access through transport infrastructure.

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

Medellín is an interesting setting to analyze spatial mismatch. Developing countries such as Colombia have income inequality and low quality jobs, which may me exacerbated by spatial mismatch (Halden, 2002; Heilmann, 2014). Compared to the capital city of Bogotá, Colombia, Medellín it has a well-developed metro system. The city has made large investments in public transport and infrastructure in the last decade, but still has a large degree of poverty and urban segregation by income. Travel times in the city have been increasing year after year 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 travel times as weights. We measure spatial mismatch for three different modes of transportation: private transport, public transport and walking. Our accessibility measure is an inverse measure of spatial mismatch since low accessibility implies larger 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 negative labor market outcomes and welfare losses. It has also pointed out to 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) evidence for developing countries. There is also evidence of SM leading to a job education mismatch (Di Paolo, Matas, & Raymond, 2017; Hensen, De Vries, & Cörvers, 2009) and to compensating differentials in the labor market, where jobs that are further away hire fewer employees with long commutes, and commuters demand for higher wages for longer commutes (Dauth & Haller, 2019; Zenou, 2009).

For developing countries, the literature has focused on measuring the costs and consequences of congestion, as well as 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 impact of public transport on informality in Sao Paulo and 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 effect of BRT system in Lima on job opportunities. In a setting in the same country we analyze, (Akbar & Duranton, 2017) study the cost of congestion in Bogotá, Colombia estimating the deadweight loss of congestion using the demand and supply of travel.

We contribute to this literature by providing a way to calculate spatial mismatch and comparing 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, and propose an adjusted accessibility measure that can be tracked over time. Other solutions to solve 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 is organized as follows: Section 2 describes the procedures we employed to capture employment and 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

In this section we present the empirical approach we use to analyze accessibility. We consider three key variables to calculate our measure: employment at workplace zones, the travel times between zones and transportation modes.

2.1 Job Accessibility

To measure spatial mismatch, 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 ignoring jobs nearby:

$$A_{i,m} = \sum_{j} \frac{emp_j}{t_{i,j,m}}, \quad t_{i,j,m} > 0. \tag{1}$$

Here, $A_{i,m}$ is the accessibility in zone i using transportation mode $m = [p, pb, w]$ representing, private vehicle, public transport and walking respectively; emp_j is the number of jobs in zone j and, $t_{i,j,m}$ is the travel time from zone i to j using mode m.

This measure counts the number jobs available in a ratio of 1 unit of travel time from an origin. Typically, we measure $t_{i,j,m}$ in minutes, so $A_{i.m}$ count how many jobs are in a 1-minute travel time circle centered on an origin in zone i through transport mode m.

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 it is the case with many developing country labor surveys– does not provide exact information for employment at each destination. We only have data on employment available for larger geographical units. Other data sources do not have information about formal and informal employment at disaggregated geographies.

To solve this problem, we suppose 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:

$$emp_i = empMed * \frac{W_h * empODC_{h(i)}}{\sum_h W_h * empODC_{h(i)}} * \frac{empOD_i}{\sum_{i\epsilon h} empOD_i}, \quad (2)$$

where emp_i is the number of jobs in the zone i, $empMed$ is the total number of jobs in the whole city, W_h is the survey weight for the larger geographical unit h , $empODC_{h(i)}$ is the number of trips to work at the commune h (where i belongs) and $empOD_i$ is the number of trips to work to destination i[1]. In our application, the smaller geographical units i are transportation zones, and the larger units $h(i)$ are communes, akin to NYC boroughs. We provide more detail 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: 2017 and 2012. For 2017 in our sample, we compute travel times for public transport and private using Google and Bing APIs respectively. For walking, we assign travel time using the euclidean distance between zone centroids and a walking speed of 4 km/ h. Walking travel times are symmetric ($t_{i,j} = t_{j,i}$) , while public and private transport travel times are not, since routes may vary by direction of travel.

Our travel time data is incomplete, because we can not compute travel times for 2012 in Google or Bing. Therefore, to compute travel times in 2012 we combine the final travel times with the variation on reported times from an Origin-Destination survey. When reported travel time variation is not available, we impute earlier travel times based on the city-wide variation. This results in the following formula.

[1] It is important to clarify that we are counting just one trip to work per person.

$$t_{i,j,m}(2012) = \begin{cases} t_{i,j,m}(2017) - (Rt_{i,j,m}(2017) - Rt_{i,j,m}(2012)) & \text{if data is available,} \\ t_{i,j,m}(2017)(1 + \%\Delta\overline{Rt_i, j, m}) & \text{if data is not available.} \end{cases} \tag{3}$$

Here, $Rt_{i,j,m}$ represents reported times and $\overline{Rt_i, j, m}$ is the mean of reported times in the entire city.

To compute travel times inside the same zone, $t_{i,i,m}$, we compute the average travel time from each zone's centroid to the edge of the zone. For each zone, let $R_{i,outside}$ denote the radius of the smallest circle that contains zone i whose center is the centroid. Let $R_{i,inside}$ denote the radius of the largest circle that can be contained in zone i centered on the zones' centroid. We calculate travel time as:

$$t_{i,i,m} = \frac{R_{i,outside} + R_{i,inside}}{2} * AVS_m. \tag{4}$$

2.4 Adjusted Accessibility

Equation (1) is not suited to analyze the evolution of spatial mismatch in an incomplete data context, where zones may not be observed in both data points or their definition may change. If there is a greater number of observed zones in a particular period, accessibility may go ub mechanically because the employment in previously unobserved zones was previously not accounted for.

We propose an adjusted measure that allows us to compare accessibility between years even if zones vary. We weight accessibility by the number of zones observed in each time period. We define adjusted accessibility as:

$$\hat{A}_{i,m} = \sum_j \frac{emp_j}{t_{i,j,m}} * \frac{1}{n_t}, \quad t_{i,j,m} > 0. \tag{5}$$

Here, n_t is the sample size in the period t. $\hat{A}_i$ can be read as the average number of jobs that can be found in a radius of 1 unit of travel time by traveling to a single destination zone. This contrasts with unadjusted accessibility, which counts jobs in every possible destination zone.

3 Data and Descriptive Statistics

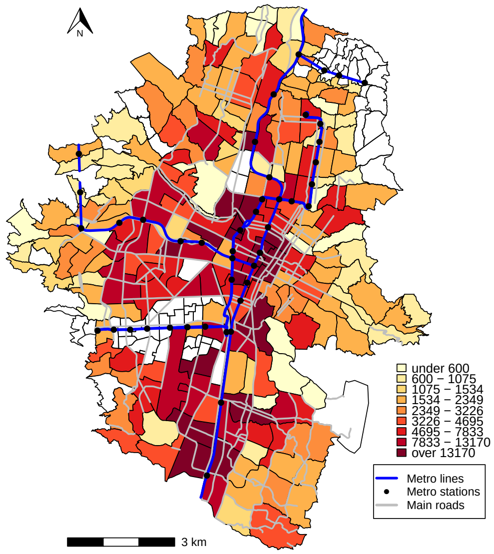
Medellín is the second largest city of Colombia. It is divided into 16 communes, and each one of them is also divided in neighborhoods. Our data is reported by integrated transport system zones (SIT zones) in each neighborhood. These zones are defined by connections with the public transportation system. A SIT zone could be based on a bus station, train station, or aerial cable station. The bulk of public transportation in Medellín is provided by the Metro system, a rapid transit system that crosses the Metropolitan Area of Medellín in all directions, and contains a train, a tram, an aerial cable car system and and a bus rapid transit system.

Our travel data comes from the Origin-Destination survey (EOD, for its acronym in spanish, "Encuesta Origen-Destino") of Medellín for the years 2012 and 2017. This survey provides information about travel times and trips in Medellín and The Metropolitan Area. It has self-reported travel times and geographies for the SIT areas or zones. We complement this reported travel time data with travel times from Bing for private vehicles and Google for public transport. This helps us mitigate measurement error in reported travel times, such as under-reporting and rounding (Carrion & Levinson, 2019). However, we use the evolution of reported travel times to measure the change in travel times across years.

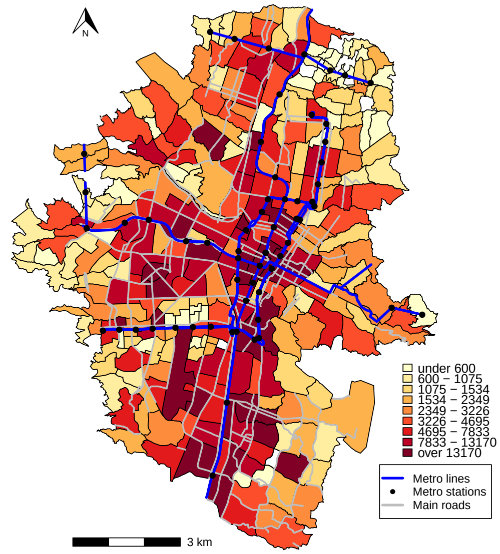
We also obtain our measure of employment by destination from the EOD data. We count the number of commuting trips that arrive at each destination zone. We then assign city employment to each zone using equation (2).

Figure 1 shows how employment is distributed in the city. For both years, employment density is highest in the south and center of the city . Medellín's center is the most commercial area of the city, whereas its south houses the industrial zone and a considerable amount of financial and entertainment services.

The spatial distribution of employment did not have a noticeable change from 2012 to 2017 in most of the city. However, there is a slight increase on density that follows new Metro system lines on the east, center and northwest of the 2017 map. According to the National Department of Statistics (DANE), during those 5 years, employment in Medellín increased by 8%, from $1'665,000$ to $1'799.000$. Because of data gaps and changes in SIT zones, there are some zones without assigned employment. There are 250 zoners in 2012 and 310 zones in 2017.



(a) Employment 2012



(b) Employment 2017

Figure 1: Spatial employment density distribution in Medellín

Source: EOD of Medellín 2012-2017 and authors' calculations.

Table 1 shows the evolution of reported travel times by transportation mode. Reported times increased for all transport modes, with increases between 14 and 20%. The increases for public and private transport can be due to congestion. The increases for walking are harder to rationalize, but could be attributed to misreporting or to additional walking as workers substitute from the other travel modes.

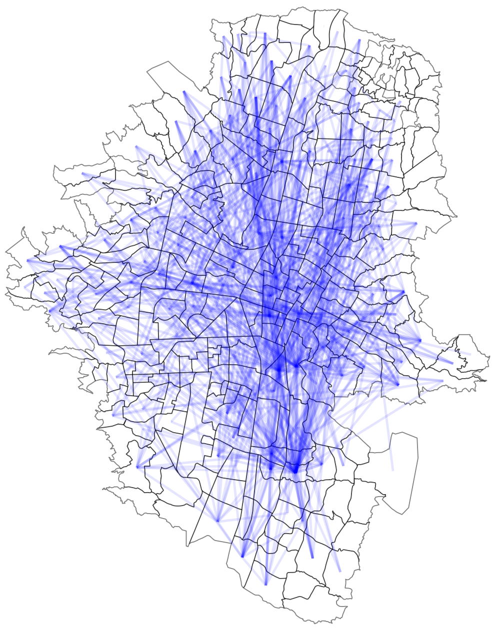
Transport	Mean 2012	Mean 2017	Diff Means	%Diff Means
Public	44.03	50.19	6.16	14.0%
Private	27.96	32.71	4.75	17.0%
Walking	15.32	18.43	3.11	20.3%

Source: EOD of Medellín 2012-2017 and authors' calculations.

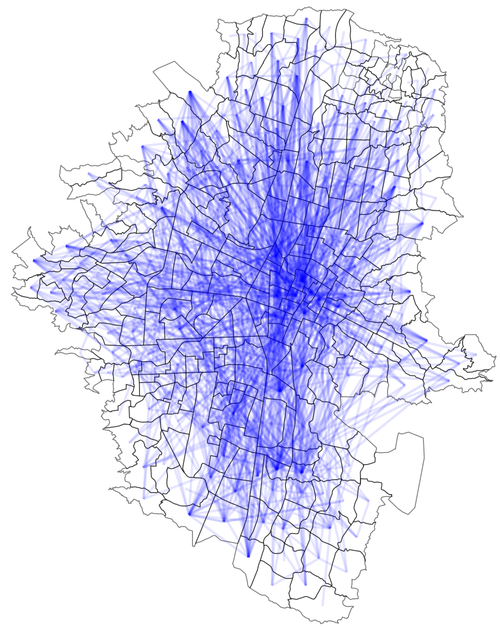
Note: Travel times are per individual. Only one trip is counted per person. The last two columns show the level and percentage difference in mean travel times by mode between 2012 ans 2017.

Table 1: Reported commuting travel times in minutes

To show some descriptive evidence of the direction of commuting in the city, Figure (2) shows the movements of people among different SIT zones for 2012 and 2017. Most of the trips are going to the center and the south of the city, and this direction of trips does not seem to change during the years. This is consistent with the employment distribution. The density of the trips seems to slightly increase in 2017 as can be seen in panel (b).



(a) Desire lines-2012



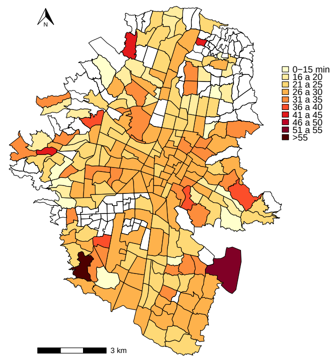
(b) Desire lines-2017

Figure 2: Desire lines for 2017 and 2012

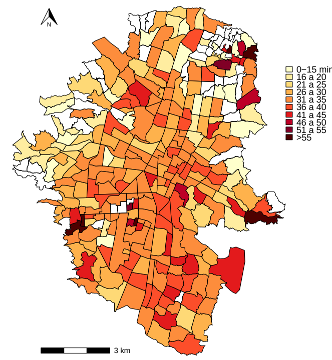
Note: Each line has an origin and a destiny. Lines are only plotted for origin-destination pairs that have more than one individual trip.

Having established where commuters go, we turn to reported travel times. Figure (3) shows the average reported travel times for each destination for public and private transport. As it can be seen, reported travel times increased for the majority of zones between 2012 and 2017.[2]

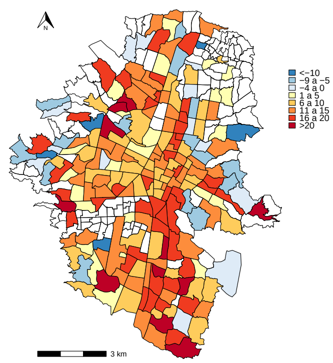
[2]In Appendix 5 we show reported travel times by walking, and also show average travel times by origin.



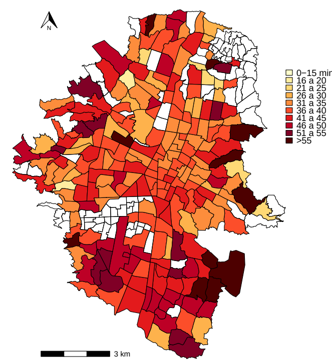
(a) Reported private times-2012



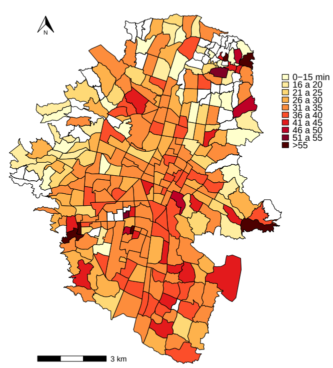
(b) Reported private times-2017



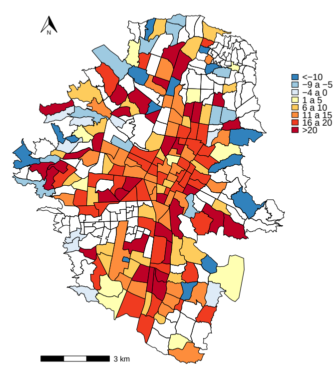
(c) Difference of reported private times



(d) Reported public times-2012



(e) Reported public times 2017



(f) Difference of reported public times

Figure 3: Reported Destination times 2012-2017 in minutes

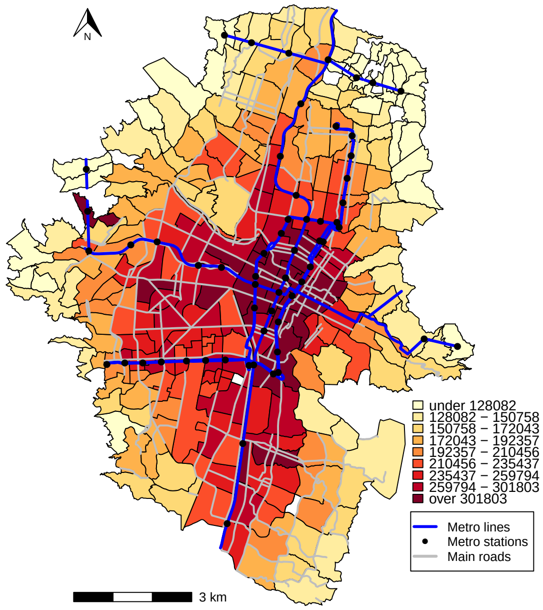
Source: EOD of Medellín 2012-2017 and authors' calculations.

4 Results

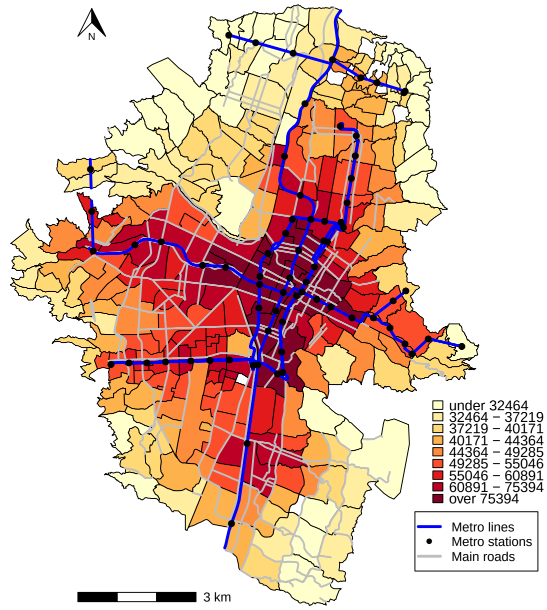
In this section we present our results for spatial mismatch in Medellín for 2012 and 2017 and its evolution over time. Our empirical approach is based on the assumption that there is always spatial mismatch. This assumption is reasonable if we take into consideration the mechanisms presented by Gobillon et al. (2007). Our accessibility measure is inversely related to mismatch, since accessibility means faster transportation or more jobs nearby.

4.1 Comparing years and modes of transport

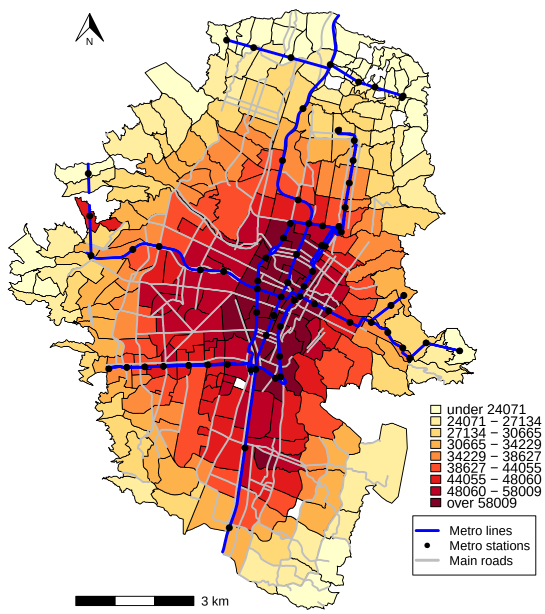
Figure (4) shows the results for $A_{i,m}$ and the three different means of transportation in 2017. As expected, zones with high employment density also tend to have high accessibility, which implies a lower mismatch. For public transportation, in many areas public transport accessibility is higher around stations of the Metro system. Therefore, Figure 4b is consistent with the Metro system being the main provider of public transportation in Medellín. For walking, panel (c) shows high accessibility in the center of the map, because of high employment density in the area. SIT zones on the center are smaller and its distances are easy to cover by walking.



(a) A_i private-2017



(b) A_i public-2017



(c) A_i walking-2017

Figure 4: Accessibility measure 2017

Source: EOD of Medellín 2012-2017 and authors' calculations.

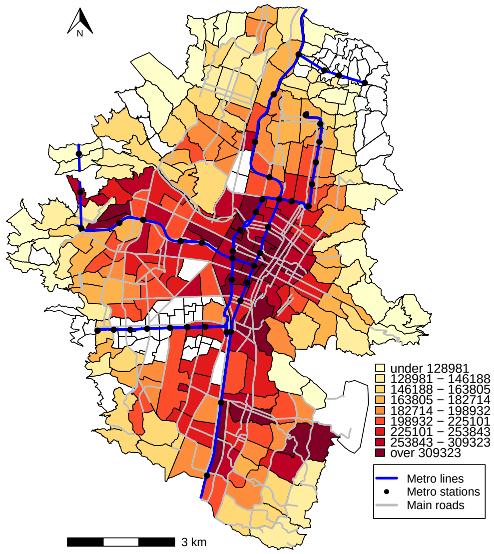
Table 2 shows detailed statistics. Accessibility using private vehicles is considerably higher than that of other transportation modes. In 2017, about 215,000 jobs could be found in a radius of 1 minute of travel time by car on average. This figure is about 4.2 times higher than accessibility in public transport. Walking gives an accessibility close to that of public transport. We note, however, that walking accessibility may be overestimated because of lack of information on real walking routes. Euclidean distances do not consider real walking routes, waiting times to cross streets and speed variations related to congestion in pedestrian routes.

	$\bar{A}_{2017}$	$\bar{A}_{2012}$	$\overline{\hat{A}}_{2017}$	$\overline{\hat{A}}_{2012}$	$Diff(\overline{\hat{A}})$	$\%Diff(\overline{\hat{A}})$
Private	$214,468.9$	$219,472.8$	691.8	881.4	-189.6	-21.5%
Public	$50,905.6$	$81,357.7$	164.2	326.7	-162.5	-49.6%
Walking	$39,807.6$	$39,311.4$	128.4	158.5	-30.1	-18.9%

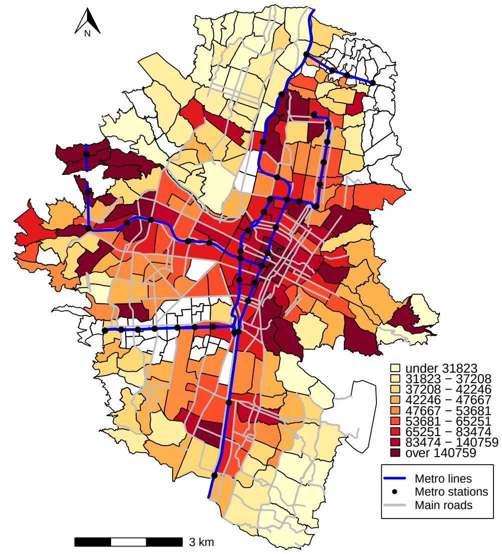
Source: EOD of Medellín 2012-2017 and authors' calculations. The first 2 columns show results for the average accessibility using equation (1). The next 4 columns offer information of the average adjusted accessibility obtained from equation (5) by year and its level and percentage differences.

Table 2: Transport and Job accessibility

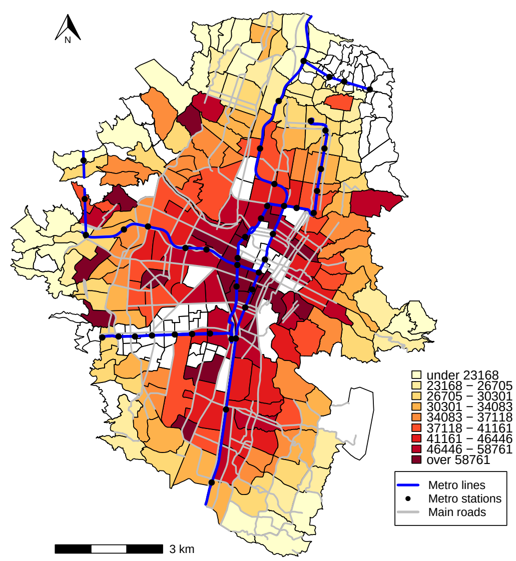
Figure 5 shows the results for 2012. There is not a big difference with 2017 in terms of distribution. However, in panel (b) accessibility seems more concentrated in zones such as the northwest, instead of areas where new metro lines appeared in 2017. Hence, it seems that Metro system can slightly impact the accessibility distribution.



(a) A_i private-2012



(b) A_i public-2012



(c) A_i walking-2012

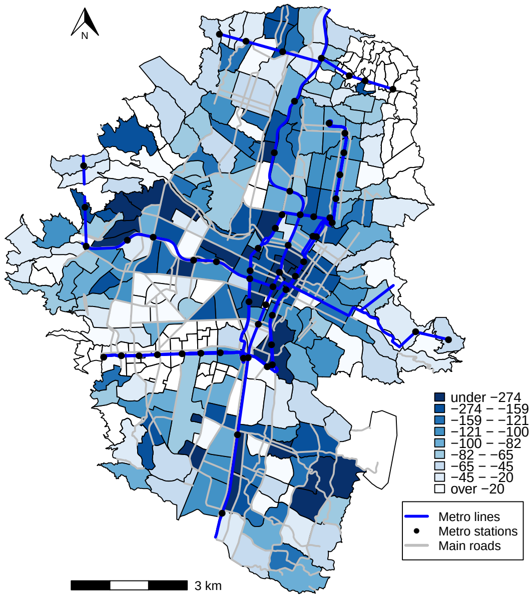
Figure 5: Accessibility measure 2012

Source: EOD of Medellín 2012-2017 and authors' calculations.

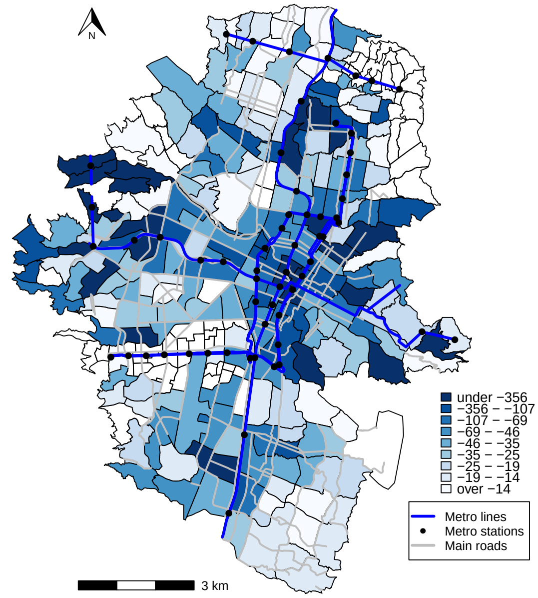
As in 2017, private transport leads to higher accessibility. Travel times in 2012 for short distances may be underestimated, since other authors have found that people under-report times for short distances (Carrion & Levinson, 2019; Li, Rose, & Sarvi, 2006; Rietveld, Zwart, Van Wee, & van den Hoorn, 1999). Nevertheless, the decrease in accessibility across years seems substantial.

To compare both measures for 2012 and 2017 we analyze the evolution of the adjusted accessibility. Figure 6 shows that average accessibility has decreased from 2012 to 2017, in fact it decreased for all the zones where we have information. Employment from 2012 to 2017 increased 8%, but even considering this higher employment, the increase in travel times offsets the increase in employment and leads to lower accessibility in 2017.

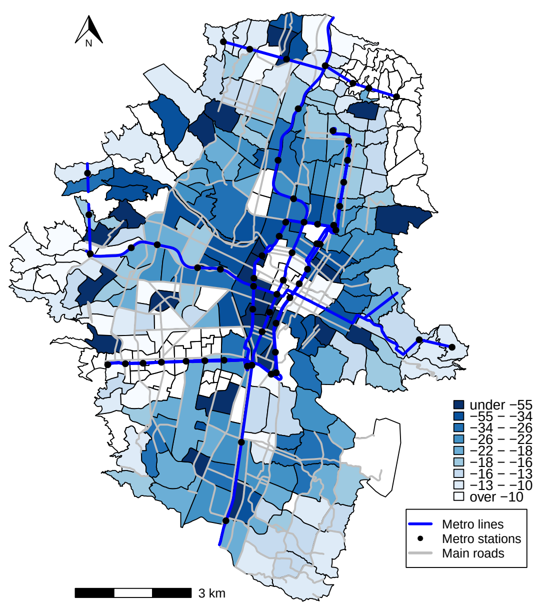
Figure 6 also shows lack of direct evidence of an increase in accessibility of areas close to the new Metro lines. We do not engage in a counterfactual analysis, but at most, we could speculate that the new metro lines only slowed down the city-wide decrease in accessibility in specific zones. Moreover, panel (b) shows that public transport accessibility is decreasing faster than private and walking accessibility.



(a) A_i Private



(b) A_i Public



(c) A_i walking

Figure 6: Difference of Adjusted Accessibility between 2017 and 2012 per SIT zone

Source: EOD of Medellín 2012-2017 and authors' calculations.

Table (2) supports the evidence of an increasing mismatch in Medellín. For private transport in 2012, you could find in average 881.4 jobs per minute of travel when moving to another zone in a single direction. By 2017, this number falls to 691.8 jobs per minute. Public transport accessibility has the highest decrease across years. This is consistent with the increase in travel times.

Another interesting result is the evolution of the accessibility gaps between public transport and private for both years. In 2012 the gap was 554.7 while in 2017 the gap was 527.2. Even though accessibility for any mode of transport has decreased, the gap between public and and private has decreased about 5%. This slighlty 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 focused on analyzing the spatial connectivity to jobs at the intra-urban level through different modes of transport. We specifically analyzed the case of Medellín, where there has been an important effort to enhance public transport infrastructure. From 2012 to 2017 the metro system expanded its operations with new bus lines like the Metroplus[3] line 2 in 2013, a new tram in the center of the city in 2016 and a new aerial cable route.

Independently of the efforts, it is clear that for both years 2012 and 2017 the accessibility obtained in private vehicle is superior than in public transport. The gap between modes was reduced in a small proportion in 2017. It seems that currently having a car or a motorcycle is a better option for going to work that using public transport. This evidence could be important in terms of environmental policies, it justifies that individuals do not have incentives to use public transport since it seems to lead to fewer access to jobs. Spatial mismatch between 2012 and 2017 increased indistinctly, increasing by a faster proportion for public transport. This increasing mismatch could not be relieved by the increasing employment density.

[3]The metro system bus rapid transit system line

We argue that that public transport and road infrastructure policies have not had the expected effect on spatial mismatch in the city. The increasing traffic, the waiting times and the impossibility of expanding many routes may have kept accessibility stagnant. Therefore, it could be useful to approach this problem from a different perspective. To avoid commuting costs and the opportunity cost of travel timem policies focused on telecommuting could be brought into play. Urban planners and policy makers should consider that having access to a private vehicle in Medellín is more efficient in terms of accessibility and that public transport policies by themselves have not had only a small impact on accessibility.

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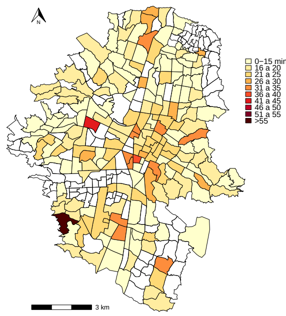
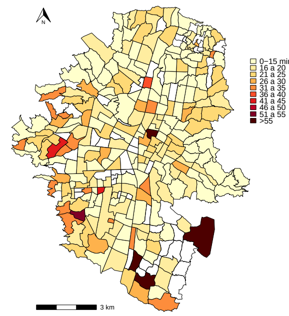
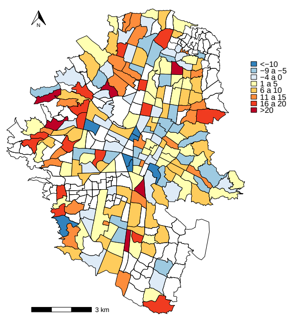
A Walking reported times



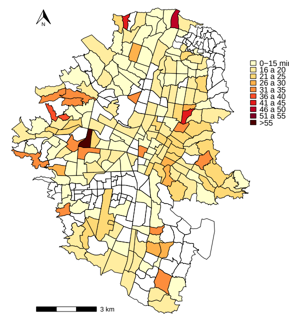
(a) Reported walking destination times-2012



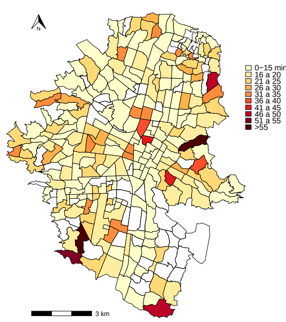
(b) Reported walking destination times-2017



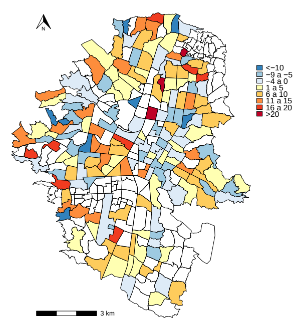
(c) Difference of reported walking times at destiny



(d) Reported walking origin times-2012



(e) Reported walking origin times-2017

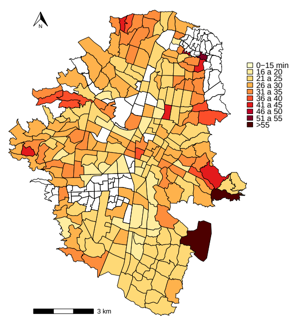


(f) Difference of reported walking times at origin

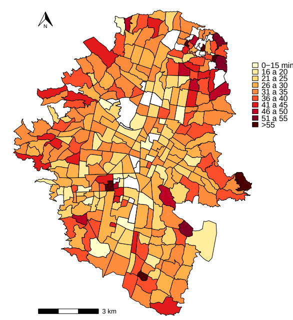
Figure 7: Reported walking times 2012-2017

Source: EOD of Medellín 2012-2017 and authors' calculations.

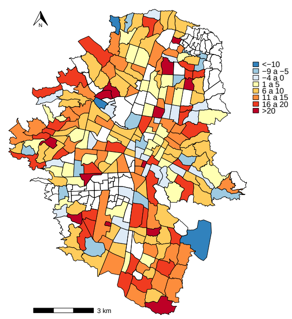
B Private and public transport reported times at origin



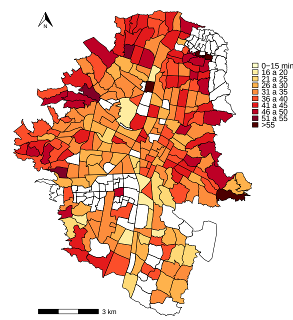
(a) Reported private origin times-2012



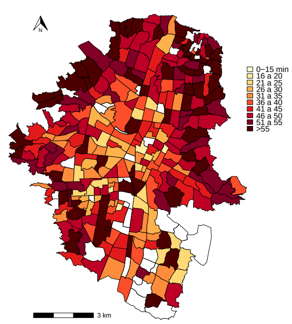
(b) Reported private origin times-2017



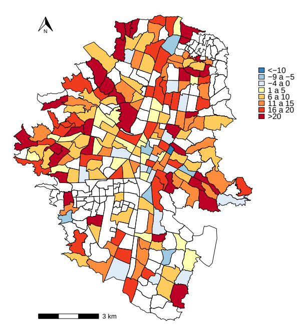
(c) Difference of reported private times at origin



(d) Reported public origin times-2012



(e) Reported public origin times-2017



(f) Difference of reported public times at origin

Figure 8: Reported private and public times 2012-2017 at origin

Source: EOD of Medellín 2012-2017 and authors' calculations.