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SPATIAL MISMATCH, WAGES AND UNEMPLOYMENT IN BRAZILIAN METROPOLITAN AREAS

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Abstract. The spatial mismatch hypothesis states that a lack of connection to job opportunities may affect an individual's prospects in the labour market, especially for low-skilled workers. This phenomenon is especially observed in large urban areas, in which low-skilled minorities tend to live far away from jobs and face geographical barriers to finding and keeping jobs. This paper aims to investigate whether this negative relationship between spatial mismatch and labour market outcomes is valid in Brazil after controlling for individual characteristics. Our conclusions indicate that there is no clear relation between different measures of accessibility to jobs and the probability of being unemployed. However, for wages there is a clear correlation, which is stronger in larger metropolitan areas in the country. Given the exploratory nature of this work, our results still rely on strong identification hypotheses to avoid potential bias related to simultaneous location decisions of workers and firms within the city. Even if these conditions do not hold, the results are still meaningful as they provide a better understanding of the conditional distribution of wages and the unemployment rate in the biggest metropolitan areas of Brazil.

1. Introduction

The spatial landscape of labour market opportunities varies significantly within an urban area. The number of job openings and the wage level tend to decline as distance to the urban centre increases. Jobs with better pay may be concentrated near the centre, as they benefit more from knowledge spillovers that generate agglomeration externalities (Partridge et al., 2009). This effect is widely acknowledged in the literature, together with additional impacts on the housing market (Lucas and Rossi-Hansberg, 2002). Furthermore, this relationship is said to be stronger for larger and denser areas, because congestion costs and the size of the urban sprawl lead to a higher cost of living for central areas. In this context, the spatial mismatch relates the structure of cities to unemployment and poverty (Gobillon and Selod, 2014).

Local labour markets can be formed by the interaction of firms and workers with heterogeneous skills in various geographical locations, given the strong connection between housing and labour markets. Geographical location gives market power to firms over potential workers, especially over those residing close to them. In their model, Brueckner et al. (2002) define two different spaces (skills spaces and urban spaces), and in equilibrium low-skilled workers will be distant from firms in both of these spaces, providing a rationale for socioeconomic ghettos (Zenou, 2009) and being consistent with the spatial mismatch hypothesis (Kain, 1968). The main mechanism underlying this model is the monopsonistic power of firms in the surroundings close to them, which depends on the elasticity of the firm's labour pool (which itself is negatively related to the costs of commuting and acquiring skills). Brueckner et al. (2002) show that workers will be separated in space by skill type, and that firms will set wages that exploit this separation in space. Low-skilled workers will therefore live far away from their jobs.

There are at least two main dimensions through which this intra-urban equilibrium in the labour market can be evaluated: unemployment and wages. According to Zenou (1999), urban efficiency wages may lead to involuntary unemployment, as they are set above the competitive equilibrium wage in order to induce workers not to shirk. Moreover, individuals living far away from jobs have poor information about job opportunities, which decreases their probability of finding a job. As a result, spatial mismatch is observed in large urban areas in which low-skilled minorities live far away from jobs and face geographical barriers to finding and keeping jobs. In addition to the spatial dimension, there is also a social separation faced by low-skilled workers and minorities (Zenou, 2013), which reduces their chances of finding a job.

Based on this theoretical perspective, this paper provides a two-fold analysis of the relationship between spatial mismatch and labour market outcomes in large metropolitan areas in Brazil. This effect is calculated through the relationship between the average wage received or the probability of being unemployed and distance to jobs (measured as the commuting time from home to work or the distance to the main business centre). This paper therefore contributes to the literature by investigating the spatial mismatch in urban labour markets in Brazil. Moreover, it shows empirically that in the Brazilian case the spatial mismatch is more relevant in relation to individual wages, while the probability of being unemployed is not as regularly distributed in space.

The paper is structured as follows. Section 2 provides a brief literature review of spatial mismatch and local labour markets focusing on social interactions within the city. In Section 3, we describe the econometric strategy and the database, while in Section 4 we analyse the results. Concluding remarks follow in Section 5.

2. Spatial mismatch and labour market equilibrium

The intra-urban spatial distribution of economic agents and production inputs has been modelled as the result of location decisions made by workers and firms (Roback, 1982). A wide range of factors, with agglomeration economies being one of them, may be included in different models, as indicated by the New Economic Geography and Urban Economics literatures (Ottaviano, 2004). The locational problem is usually analysed by evaluating how local prices (rents and wages) relate to the distance from the Central Business District (CBD) of the city (Lucas and Rossi-Hansberg, 2002). Distance to multiple tiers of the urban hierarchy within a city can also be relevant for this analysis (Partridge et al., 2009).

More recent developments combine the concept of spatial mismatch with the analysis of local prices within a city and the embedded location decisions of workers and firms. Spatial mismatch in the labour market means that people face spatial frictions when accessing jobs in metropolitan areas (Houston, 2005a). This phenomenon relates to the way in which low-skilled minorities are affected by distance to job locations (Zenou, 2009). The resulting distributions arise from the equilibria in the labour and the housing markets, which are simultaneously determined by the different decisions made by firms and workers.

The spatial mismatch hypothesis argues that low-skilled minorities face poor labour market outcomes because they are disconnected from job opportunities within the city (Gobillon et al., 2007). Usual applications of this hypothesis look at the case of afro-descendent population or other minorities in US cities, who often live far away from low-skilled jobs that are available in the suburbs of American cities (see for instance Ihlanfeldt, 2006, Zenou, 2009, and Andersson et al., 2014).

The range of mechanisms underlying the theoretical frameworks that generate spatial mismatches are related either to the labour market itself or to the factors that potentially explain why minorities are physically disconnected from jobs (Gobillon and Selod, 2014). According to Gobillon et al. (2007), these mechanisms can be analysed separately for workers and firms. From the workers' perspective, they are the following:

(i) long commuting may lead a worker to refuse a job opportunity after carrying out a cost-benefit analysis;

(ii) search efficiency may decrease with distance to jobs;

(iii) search intensity may also be affected by distance to jobs; and

(iv) high search costs may cause workers to restrict their search to a limited area.

From the firms' perspective, the main mechanisms are:

(v) stigma or prejudice may make firms discriminate against workers who live in certain locations;

(vi) employers may pay lower wages or refuse to hire workers who commute for long distances, as the commuting may decrease their productivity; and

(vii) employers may have a prejudice against specific workers because of the expected preferences of their customers.

As mentioned above, the spatial mismatch hypothesis is usually considered in the specific case of low-skilled minorities living in urban centres. However, the concept of a 'spatial mismatch' in general terms is broadly used to investigate the uneven locations of jobs and individuals that lead in an endogenous way to different levels of unemployment and wages across a city.

Among some of the theoretical models devoted to describing spatial mismatches in the urban environment, Zenou (2000) develops a model with endogenous city formation mechanisms that result in jobs concentrating in the CBD, employed individuals residing in the vicinity of the city centre, and the unemployed being further away from jobs. Urban unemployment will then be reinforced in the outskirts of the city, because the further away an individual is from jobs (which are concentrated in the CBD), the harder it is for her or him to find a job. Within a similar setting generated from a model based on a monocentric city combined with an efficiency wage mechanism and high reallocation costs, wages are expected to decrease with distance to the centre, as demonstrated by Zenou (2006).

It is important to note that the modelling of metropolitan labour markets can be significantly different for low-skilled and high-skilled workers, given the more limited distance that low-income individuals can commute. Thus, low-skilled workers will face a segmented urban labour market, while for high-skilled workers space is less restrictive. Unemployment for low-skilled workers will be associated with the lack of jobs in the areas close to their residence, while high-skilled workers will search for jobs in a wider spatial scale (Morrison, 2005). Therefore, for high-skilled individuals, urban landscape is expected to have a smaller impact on their labour market outcomes. These two mechanisms can co-exist within the city to generate the observed distribution of unemployment rates.

Despite the large amount of empirical literature, Houston (2005b) argues that there is no clear consensus on the importance of the spatial mismatch in the explanation of labour market outcomes. The duration of unemployment is the labour market outcome used by Andersson et al. (2014) to measure the effects of spatial mismatch. They consider a matched employer–employee database, and build person-specific measures of job accessibility with an empirical model of transport modal choice and network travel-time, finding that better job accessibility helps to decrease the duration of joblessness for lower-paid workers. Moreover, under-privileged groups (black people, women and older people) are more affected by the lack of accessibility.

The total number of jobs available in each region of the city and the impedance for reaching those regions can be used to define accessibility to jobs in a specific location. The impedance measure is usually defined either by the Euclidean distance or by commuting time between residential location and jobs, which may be derived from transport availability in each area of the city. The latter approach is followed by Vieira and Haddad (2015) for the São Paulo Metropolitan area, and they find indications that accessibility and income are strongly and positively related in the city. Di Paolo et al. (2016) find that car availability is relevant for job–education mismatch and that public transportation has an effect on better matching in the labour market for each schooling level.

Åslund et al. (2010) calculate the accessibility measure by considering the number of jobs and the number of people of working age within a 5 km radius of the individual's residential location. They then consider the exogenous allocation of refugees in Sweden ten years before and build an instrument that is based on how accessible jobs are to immigrants in their arrival year, and they find a positive correlation between local job proximity and individual outcomes.

Job accessibility, demand and supply in the Chicago metropolitan area are used by Hu (2014) to find that socioeconomic restructuring (an increase in poverty and a reduction in relevant job opportunities) negatively affects poor job seekers, while spatial transformation (when jobs and job seekers move to the outskirts of the city) has a positive effect on their job prospects. The latter effect is caused by poorer individuals following jobs to suburban areas. With a similar empirical strategy, Hu and Giuliano (2014) find no relationship between spatial accessibility and the unequal employment status of the poor in the Los Angeles metropolitan area.

According to Tyndall (2015), public transportation has a causal and negative effect on neighbourhood unemployment rates, particularly for groups who are more dependent on this mode of transport. Their conclusions come from a natural experiment derived from Hurricane Sandy, which exogenously reduced access to public transport in some neighbourhoods in New York City.

The empirical literature on spatial mismatch can be subdivided into two main strands: the first aims to understand the causes, while the second discusses the consequences of a spatial mismatch (Gobillon and Selod, 2014). According to Houston (2005b), the consequences of a spatial mismatch are usually evaluated through an analysis of (i) residential segregation, (ii) comparisons of commuting times, (iii) comparisons of earnings, and (iv) measures of job proximity.

Following the same line of thought, Ihlanfeldt (2006) highlights the fact that the effects of spatial mismatch have been investigated on lower earnings, longer commutes and higher unemployment, especially in the case of black workers in the United States. Usually, employment and earnings equations include measures of local job opportunities, with a strategy based on a gravity model with a distance-decay function to take account of being further away from job opportunities.

According to Ihlanfeldt (2006), among the main econometric problems arising from this strategy there is the fact that residential location and the measurement of job opportunities are potentially endogenous. Such endogeneity may appear through the self-selection of more or less productive workers to specific areas, by the potential reverse causality of job opportunities and the probability of being unemployed, or through the simultaneous location decisions of firms and workers in a general equilibrium setting.

One can deal with the simultaneity issue by including historical or geographical instruments that influenced the location of transportation infrastructure within a city without directly determining the location of workers and firms. This approach is explored by Haddad and Barufi (2016) for São Paulo Metropolitan Region with river shore access as an instrument, but is not replicable for the whole country as such detailed geographical information is not available yet in a larger scale.

Our identification strategy will be based in more restrictive hypotheses. In the short run, prices in the labour market are assumed to be close to the equilibrium level, and workers and firms are relatively immobile (Gibb et al., 2014). This endogeneity issue is then expected to be less relevant in the case of labour market outcomes. In addition, the measurement of local job opportunities can be indirect (using the assumption that there is a geographical centre in the city or by considering commuting time as a possible measure of the distance to jobs). The specific location of job opportunities is then not included in the analysis, meaning that this endogeneity issue can be less relevant. In this study, we will assume that these aspects are able to soften such concerns. In any case, the potential direction of an endogeneity bias will be discussed in the following sections.

Furthermore, usual measures of spatial mismatch may be problematic (Houston, 2005b). On the one hand, long commutes may be a sign of either high mobility (highly paid workers) or a spatial mismatch between workers and jobs. On the other hand, different groups have specific propensities to commute, which means that studies usually measure commuting patterns of employed individuals, while spatial mismatch is generally concerned with the unemployed, who may behave differently. The author also suggests that job accessibility should take into account not only distance but also the amount of competition for the accessible jobs. Finally, total travel burden should take into account time, pecuniary cost and inconvenience (Bruzelius, 1979). Commuting time, cost or distance are therefore, by themselves, incomplete measures.

In summary, the empirical literature finds some mixed results, especially regarding the relationship between different measures of spatial mismatch and the unemployment rate. However, an increase in accessibility to jobs seems to improve labour market outcomes, especially for low-skilled minorities for whom the spatial mismatch is more relevant. There are significant empirical issues related to the estimation of this effect, whose consequences will be further discussed.

The next section will present our empirical strategy, which deal with comparisons of earnings and measures of job proximity (items (iii) and (iv) discussed above and listed by Houston, 2005b). In addition, we focus on the probability, for each economically active individual, of being unemployed, according to his or her residential location. To compare earnings, the unavailability of data means that we measure wages from a residential location perspective instead of a workplace basis, even if the latter would be a more appropriate approach (Houston, 2005b).

3. Empirical strategy and data

The empirical strategy developed here is based on the estimation of the relationship between different measures of distance to jobs and labour market outcomes (earnings and the probability of being unemployed). All dependent variables are residence-based, due to data availability. Such strategy aims at exploring different dimensions of the spatial mismatch hypothesis in Brazilian metropolitan areas

Estimations are conducted for individuals residing in a specific metropolitan area in order to capture the effect of each variable in relative terms within a specific urban structure. We assume that the wage equation can be written as follows:

$$w_i = \propto + \beta X_i + \gamma_1 inv\_dist_r + \gamma_2 inv\_dist_r^2 + \varepsilon_i \qquad (1)$$

where w_i is the logarithm of the hourly wage measured for employed individuals who do not work at home, and X_i includes age, age squared, sector of activity, occupation, formalization status of the job, colour or race, education level, whether the individual is married, whether he or she has at least one child younger than fifteen living in the house, whether the house is owned by the family and whether the person is or is not the head of the household. In addition, inv_dist_r refers to the inverse of the Euclidean distance from the centroid of the weighting area to the main business centre.[1]

An alternative formulation for the reduced form presented in (1) is given by:

[1] Under the simplifying assumption of a monocentric city, we consider the inverse distance from the weighting area[1] where the individual lives to the main business centre of the metropolitan area, to calculate an approximate measure of distance to jobs.

$$w_i = \propto + \beta X_i + \theta_1 time\_commut\_6\_30_i + \theta_2 time\_commut\_31\_60_i + \theta_3 time\_commut\_61\_120_i + \theta_4 time\_commut\_121\_more_i + \varepsilon_i \qquad (2)$$

In this case, instead of the inverse distance to the centre, commuting time from home to work is used to evaluate the relationship between wages/productivity and the urban landscape.[2] All these models are estimated with a simple OLS.

Another dimension of spatial mismatch is the heterogeneity in the unemployment rates within the urban area. This dimension will be assessed by estimating the probability of being unemployed for each economically active individual, given her or his relative location to the main centre of the city:

$$h_i = P[U_i = 1] = F[\beta X_i + \gamma_1 inv\_dist_r + \gamma_2 inv\_dist_r^2] \qquad (3)$$

In this specification, U_i refers to the employment status (it equals 1 when a person is unemployed) and F is a logistic cumulative probability function. Here, X_i is the set of observed characteristics for the individual (age, age squared, colour or race, education level, whether the individual is married, whether he or she has at least one child younger than fifteen living in the house, whether the house is owned by the family and whether the person is or is not the head of the household). Finally, β is a vector of parameters, and inv_dist_r is measured as before. An alternative formulation is the following:

$$h_i = P[U_i = 1] = F[\beta X_i + \theta_1 \%\_time\_commut\_6\_30_r + \theta_2 \%\_time\_commut\_31\_60_r + \theta_3 \%\_time\_commut\_61\_120_r + \theta_4 \%\_time\_commut\_121\_more_r] \qquad (4)$$

In this case, the spatial mismatch is approximated by the percentage of individuals in the neighbourhood whose time spent in commuting belongs to a particular time span.

Apart from the whole database, these four models will be estimated for three separate groups: (i) individuals who did not complete primary school[3], (ii) high school graduates without college degree, and (iii) individuals who completed college education. In a country such as

[2] This impedance measure is the commuting time from home to work, calculated at the individual level for the wage equation or for the neighbourhood in the case of the estimation of unemployment probability. This second approach may be associated with a multicentric city structure.

[3] 8 years of education.

Brazil, inequality derived from the spatial mismatch can be more or less pronounced depending on the city size and the distance to the main concentration of job opportunities, and it may affect distinct skilled groups in different ways.

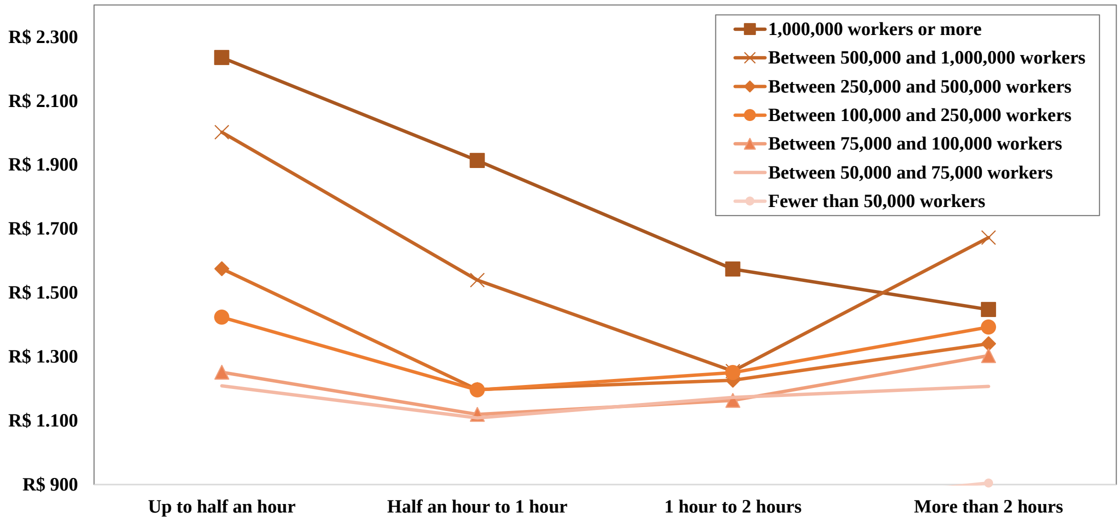
3.1. Database

The Brazilian Institute of Geography and Statistics (Instituto Brasileiro de Geografia e Estatística – IBGE) conducts a Demographic Census every ten years, with regional disaggregation at the municipal level (or at the census area level for bigger municipalities). The Demographic Census collects information on the main characteristics of individuals and households, providing details on the living conditions of the population in each municipality, and serving as a very important policy instrument in a country with a land area the size of Brazil. A shorter questionnaire applies to the whole population at the census tract level, while specific individual characteristics are investigated in a longer set of questions that are given to a sample and are representative at the weighting areas level (conglomerates of census tracts with at least 400 households). Microdata at the individual level are available for this sample. We will use weighting areas as our definition of neighbourhood.

3.2. Descriptive Statistics

The problem at hand is fundamentally metropolitan, as commuting costs and agglomeration economies become more relevant at a larger urban scale (Partridge et al., 2009). In fact, if one considers the average wage received by workers according to their commuting time from home to work, it is noticeable that the negative relationship between these two variables is clearer when cities with at least 500,000 workers are taken into account (Figure 1).

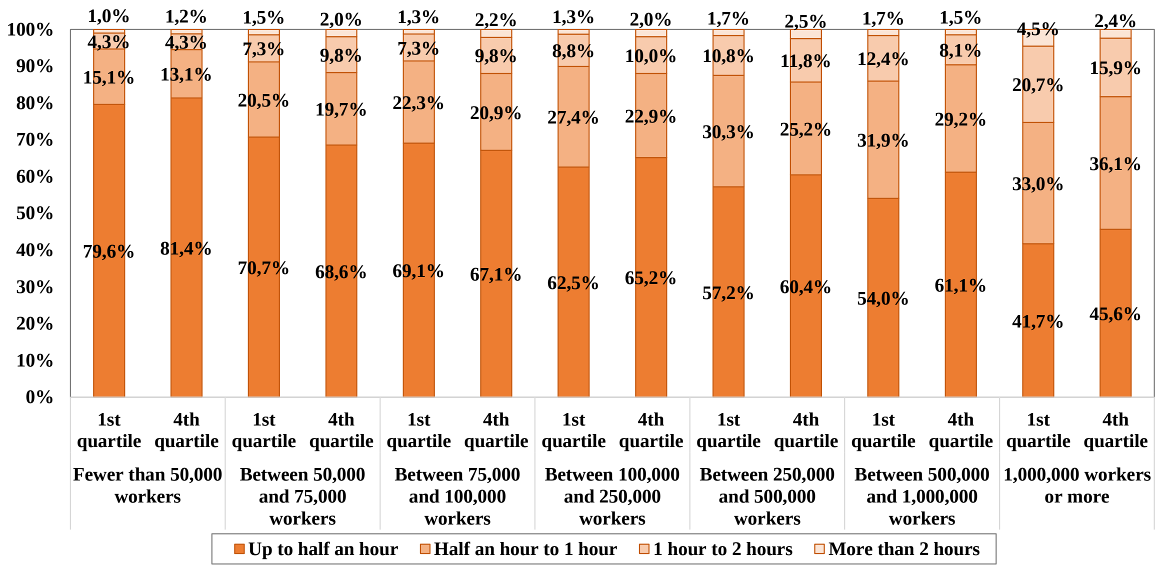
Figure 1. Average Wage of Workers according to their Commuting Time from Home to Work and the Size of the Municipality of Residence, 2010



Source: IBGE.

This difference between cities of different sizes is made clear in the analysis presented in Figure 2. In fact, the biggest differences in commuting times faced by workers in the richest (4^{th}) and the poorest (1^{st}) quartiles of the wage distribution in each municipality is seen in places with at least 500,000 workers. Furthermore, the decreasing relationship between wages and commuting time is stronger for those who commute for up to two hours.

Figure 2. Distribution of Workers who Commute from Home to Work and Belong to the 1st Quartile and the 4th Quartile of the Wage Distribution (according to their commuting time and the size of the workforce in the municipality of residence), 2010



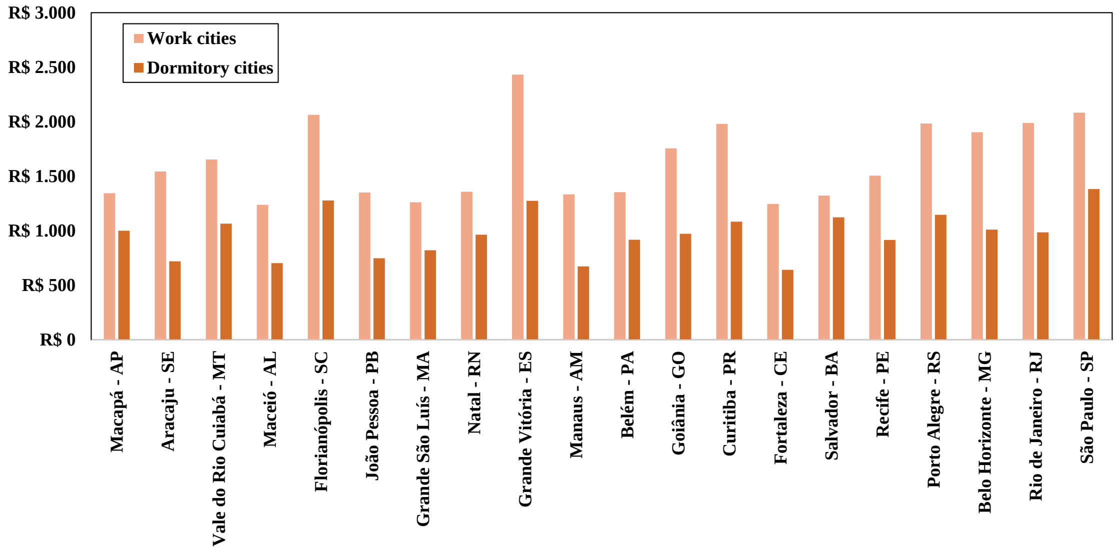
Source: IBGE.

For this reason, only 20 metropolitan areas containing state capitals were included in the study. In addition, only male workers aged 25 to 64 years old were kept in the database, in order to homogenise their decisions to participate in the labour market. For the wage regression, the database contained only workers who commuted to work and returned home every day.

It is also possible to show how wages and the unemployment rate vary according to the distance between the residential location of a worker and the centre of the city. Considering the daily commuting flows from home to work obtained from the Demographic Census of 2010, it is possible to define work cities and dormitory cities in each metropolitan area. The former are characterized by a higher inflow of people going there to work than an outflow of those who live there and go somewhere else to work, while the latter present a higher daily worker outflow than an inflow.

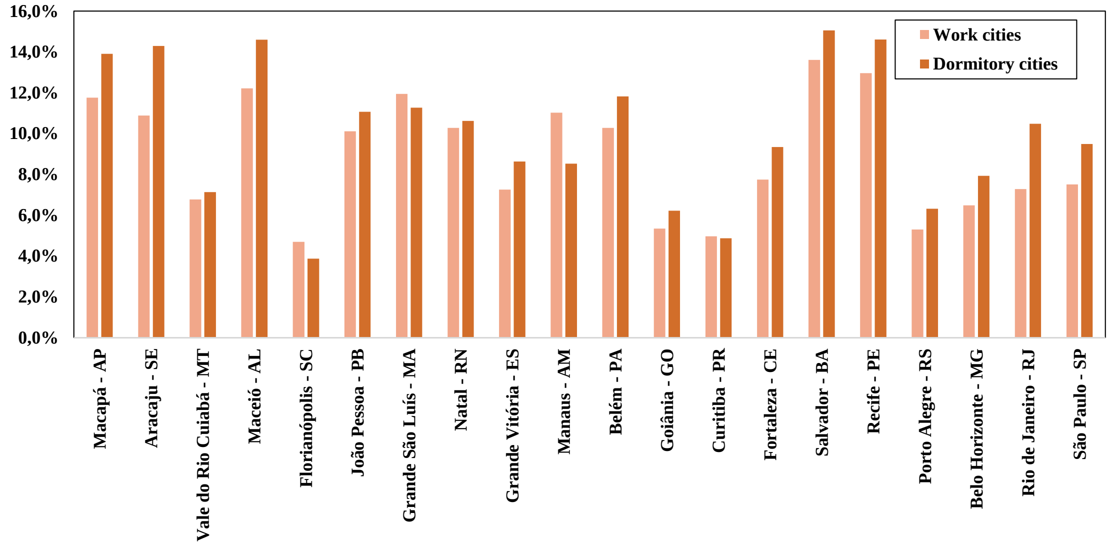
Figure 3 shows that average wages are much higher for people who live in work cities than for people who live in dormitory cities. However, in the case of the unemployment rate, there are mixed signs (Figure 4). In some metropolitan areas (Manaus, Grande São Luís, Florianópolis and Curitiba), dormitory cities show a lower unemployment rate than work cities. This pattern is unexpected under the hypothesis of a monocentric metropolitan area, but may be associated to the fact that these specific metropolitan areas are less dense than other more developed metropolitan areas in Brazil, for which the unemployment rate is larger in dormitory cities.

Figure 3. Average Monthly Wage for Workers who Live in Work or Dormitory Cities inside each Metropolitan Area (ordered by the size of working population), 2010



Source: IBGE.

Figure 4. Average Unemployment Rate for People who Live in Work or Dormitory Cities inside each Metropolitan Area (ordered by the size of working population), 2010



Source: IBGE.

The econometric discussion outlined above explains the need to calculate the distance of each weighting area to the relevant business centre. This should be done on the basis of the main location of jobs around the city. In Brazil, however, there is no consolidated database covering all metropolitan areas and showing the location of jobs. Therefore, we consider a different approach, in which the number of jobs in 2010[4] in each municipality that forms the metropolitan area is used as a weight for the geographic coordinates of the official political centre of this municipality. Thus, it is possible to calculate the weighted geographical centre of each metropolitan area.

[4] Data obtained from the Ministry of Labour and available at http://pdet.mte.gov.br/acesso-online-as-bases-de-dados .

Table 1. Descriptive Characteristics of each Metropolitan Area (ordered by the size of working age population), 2010

Metropolitan region	Macro-region	Average hourly wage (R$ 2010)	Unemployment rate	Percentage of individuals commuting for more than 1 hour	Working age population (men aged 25-64)
Macapá - AP	North	R$ 10,44	7,7%	5,3%	85.494
Aracaju - SE	Northeast	R$ 10,87	7,4%	10,7%	159.838
Vale do Rio Cuiabá - MT	Centre-West	R$ 13,58	4,3%	7,7%	160.638
Maceió - AL	Northeast	R$ 9,27	8,2%	13,3%	216.904
Florianópolis - SC	South	R$ 13,77	2,6%	6,6%	217.208
João Pessoa - PB	Northeast	R$ 9,72	6,5%	7,7%	230.930
Grande São Luís - MA	Northeast	R$ 10,96	7,5%	16,1%	244.017
Natal - RN	Northeast	R$ 9,85	7,1%	8,4%	258.207
Grande Vitória - ES	Southeast	R$ 11,94	4,9%	14,6%	353.561
Manaus - AM	North	R$ 11,19	7,1%	16,7%	378.496
Belém - PA	North	R$ 10,85	7,0%	14,4%	402.170
Goiânia - GO	Centre-West	R$ 12,32	3,4%	11,2%	415.541
Curitiba - PR	South	R$ 13,51	3,0%	13,1%	623.103
Fortaleza - CE	Northeast	R$ 9,41	5,6%	12,4%	666.504
Salvador - BA	Northeast	R$ 11,01	9,2%	20,0%	723.297
Recife - PE	Northeast	R$ 10,00	9,5%	17,2%	745.952
Porto Alegre - RS	South	R$ 12,38	3,7%	11,4%	807.268
Belo Horizonte - MG	Southeast	R$ 11,82	4,2%	18,7%	1.115.715
Rio de Janeiro - RJ	Southeast	R$ 12,92	5,8%	30,5%	2.402.075
São Paulo - SP	Southeast	R$ 15,37	5,7%	28,8%	3.953.270

Source: IBGE.

Focusing more specifically on the models, the main descriptive characteristics are presented in Tables 1, 2 and 3, and Tables A.1, A.2 and A.3 (in the Appendix). Table 1 indicates that the metropolitan areas considered in this study are significantly heterogeneous and should be treated separately, as each of them has a specific distribution of jobs and wages. Furthermore, areas with a bigger labour market have a higher average wage and a higher percentage of workers who commute for more than one hour to reach their jobs. This characteristic is clearer for metropolitan areas with more than a million male workers aged 25 to 64. For the unemployment rate, there seems to be more of a regional aspect to the level observed in each metropolitan area, as regions located in the Northeast, for example, show a much higher level of unemployment than other regions.

There is a strong relationship between commuting time and distance to the centre, as can be seen in Table 2. In São Paulo and Rio de Janeiro, the biggest metropolitan areas in Brazil, the percentage of individuals who commute for more than one hour is significantly higher for people who live more than 2.5 km from the centre than for those living less than this distance away. However, this percentage decreases when the distance to the centre is greater than 10 km, becoming almost negligible for people living more than 30 km from the centre. This is an indication that, for most metropolitan areas, after a certain distance from the centre people will interact more with local labour sub-markets. Since our objective is to investigate labour market characteristics related to the main business centre of each metropolitan area, we will focus on individuals living within a circle with a radius of 30 km.

Table 2. Percentage of Workers who Spend More than One Hour Commuting from Home to Work According to the Distance the Worker Lives from the Centre, (ordered by the size of working population), 2010

	Less than 2.5 km	2.5 km to less than 5 km	5 km to less than 10 km	10 km to less than 20 km	20 km to less than 30 km	30 km to less than 40 km	40 km to less than 50 km	50 km or more
Macapá - AP	3.6%	8.0%	2.2%	0.0%		0.0%		4.0%
Aracaju - SE	6.5%	12.9%	7.1%	0.0%				
Vale do Rio Cuiabá - MT	3.1%	11.3%	4.9%	2.2%	0.0%			8.7%
Maceió - AL	5.9%	18.5%	24.3%	3.3%	6.6%	0.0%		
Florianópolis - SC	3.1%	7.5%	9.2%	7.1%	2.3%	2.2%	2.1%	2.4%
João Pessoa - PB	7.7%	14.2%	1.7%	3.5%	4.0%	12.6%	2.7%	7.7%
Grande São Luís - MA	8.0%	43.6%	18.0%	4.5%	1.2%	0.0%		
Natal - RN	11.7%	8.1%	5.4%	2.9%	4.2%	0.0%		
Grande Vitória - ES	6.7%	40.3%	16.2%	6.6%	2.6%	17.6%	1.1%	4.2%
Manaus - AM	9.3%	34.0%	28.6%	0.0%			0.0%	11.4%
Belém - PA	7.0%	10.1%	44.6%	2.3%	10.8%	4.5%	0.0%	
Goiânia - GO	3.4%	12.7%	24.1%	1.8%	18.1%	5.4%	1.7%	8.2%
Curitiba - PR	3.7%	39.8%	16.7%	7.2%	1.8%	42.6%	4.8%	8.7%
Fortaleza - CE	16.9%	26.8%	8.4%	1.1%	6.8%	5.9%	2.8%	6.1%
Salvador - BA	24.1%	26.9%	11.9%	4.0%	8.5%	5.1%	4.1%	10.0%
Recife - PE	7.3%	36.2%	28.5%	4.3%	7.4%	5.2%	0.0%	
Porto Alegre - RS	6.5%	28.5%	39.6%	7.2%	3.0%	3.3%	1.2%	7.8%
Belo Horizonte - MG	11.8%	51.1%	34.3%	8.0%	5.4%	10.3%	12.1%	6.5%
Rio de Janeiro - RJ	15.8%	62.3%	70.9%	29.1%	16.2%	20.9%	8.7%	22.8%
São Paulo - SP	19.3%	80.7%	87.1%	21.5%	11.0%	5.0%	1.6%	16.9%

Source: IBGE.

In Table 3, we can note that the wage level is higher for older individuals, those who are better educated, married people, those who are Indians, from Asiatic ancestry or white, those who are the head of a household, people employed in the formal sector and those who work in health and social services or leaders, scientists or artists. In addition, workers who commute for a longer time have a lower salary, on average. On the other hand, the unemployment rate is higher for younger individuals, those who are less educated, those who are black or brown, single people, people with no children, and those who are not heads of households.

Table 3. Descriptive Statistics by Individual Characteristics,[5] 2010

	Unemp. Rate	Average hourly wage (R$ 2010)		Unemp. Rate	Average hourly wage (R$ 2010)
Age			Sector		
25 to 34 years old	7,4%	R$ 9,75	Agriculture		R$ 7,51
35 to 44 years old	4,9%	R$ 12,31	Manufacture and construction		R$ 9,59
45 to 54 years old	4,7%	R$ 15,48	Other industrial activities		R$ 14,26
55 to 64 years old	4,7%	R$ 19,06	Commerce		R$ 10,26
Education level			Services		R$ 10,53
Less than 7 years of schooling	6,9%	R$ 6,62	Auxiliary services		R$ 17,83
8 to 10 years of schooling	6,3%	R$ 8,29	Transport and communication		R$ 9,86
11 to 14 years of schooling	5,7%	R$ 11,21	Health and social services		R$ 24,84
15 years of schooling or more	3,0%	R$ 33,37	Education		R$ 17,85
Colour			Public sector		R$ 22,01
White	4,8%	R$ 16,91	Other activities		R$ 15,79
Black	6,8%	R$ 8,43	Occupation		
Yellow	5,1%	R$ 18,20	Non-applicable		R$ 16,80
Brown	6,7%	R$ 8,84	Leaders		R$ 30,45
Indigenous	6,4%	R$ 8,97	Scientific, artistic or similar		R$ 30,88
Marital status			Technical level		R$ 14,93
Single	7,7%	R$ 10,08	Administrative service		R$ 9,61
Married	3,7%	R$ 15,48	Commerce and service		R$ 7,14
Children			Agriculture, livestock, extractive activities		R$ 4,14
No children up to 15 years old	6,9%	R$ 13,07	Manufacture		R$ 7,26
Has at least one child up to 15 years old	4,1%	R$ 12,29	Military		R$ 23,73
Home ownership			Commuting time to work		
Tenant	5,4%	R$ 11,39	Up to 5 minutes		R$ 13,66
Owned home	5,9%	R$ 13,21	6 to 30 minutes		R$ 13,47
Household position			31 minutes to 1 hour		R$ 12,68
Another member of the household	8,0%	R$ 10,36	More than 1 hour to 2 houres		R$ 11,27
Head of the household	4,2%	R$ 14,33	More than 2 hours		R$ 11,15
Formality status					
Informal sector		R$ 9,46			
Formal sector		R$ 13,93			

Source: IBGE.

The theory of spatial mismatch states that a lack of connection to job opportunities may affect an individual's prospects in the labour market, especially for low-skilled workers. Complementing the results presented in Table 3, Tables A.1, A.2 and A.3 provide wage levels and unemployment rates using different impedance measures. Distance to jobs can be calculated in many ways: (i) distance from the centroid of the weighting area to the business

[5] The unemployment rate is calculated for the weighting area in which the individual resides.

centre of the metropolitan area; (ii) individual commuting time from home to work; or (iii) percentage of workers in the weighting area whose commuting time falls within each time span. For the wage equation, we consider alternatively (i) and (ii) for employed individuals. On the other side, for the estimation of the probability of unemployment, (i) and (iii) are used, calculated at the weighting area level.

With these considerations in mind, Tables A.1, A.2 and A.3 show that wages seem to be higher near the centre of each metropolitan area, and that this effect is stronger in larger areas. However, for the unemployment rate, the expected positive relationship with distance to jobs is not clear. The main results will be presented in the next section.

4. Results

The first set of results refers to the estimation of wage equations that control for individual characteristics and uses two different measures of relative distance in the city: the distance to a unique centre (a monocentric city) and the distance to each worker's job (a multicentric city).

Table 4 shows that wages have a positive relationship with the inverse distance to the main centre of each metropolitan area (and, as a consequence, a negative relationship with distance itself). This effect is more significant for larger metropolitan areas, and it seems to be stronger for individuals with a higher education level. Therefore, wages are lower for individuals who live further away from the main business centre. However, this result demonstrates more of a correlation than a causal effect, especially because individuals are analysed with reference to their residential location. There may be inverse causality in this case, as an individual's choice of location may be affected by the wage previously received, and this may also affect current labour market prospects and productivity.

This issue may also be present when the spatial mismatch is captured by each individual's commuting time from home to work (Table 5). The estimated coefficients are then likely to be underestimating the real effect. Therefore, if this reverse causality issue is correctly dealt with, distance to jobs should be even more relevant in determining wage levels, as it would be possible to discount the effect of relocation by looking at job opportunities over the city.

Table 4. OLS Regressions of the Logarithm of the Hourly Wage (for all individuals and by education group)

	Macapá - AP	Aracaju - SE	Vale do Rio Cuiabá - MT	Maceió - AL	Florianópolis - SC	João Pessoa - PB	Grande São Luís - MA	Natal - RN	Grande Vitória - ES	Manaus - AM
All individuals										
Inverse of distance	0.396***	0.502***	0.419	0.365***	0.112**	0.128	0.250**	-0.606***	0.133***	0.273***
Inverse of distance squared	-0.207**	-0.338**	0.378	-0.050***	-0.041	-0.265	-0.182***	0.554***	-0.035***	-0.060***
N	5.559	7.736	8.121	9.068	15.481	10.828	10.680	12.056	24.887	11.912
Adjusted R squared	0.429	0.462	0.368	0.450	0.418	0.442	0.356	0.458	0.430	0.339
Up to incomplete primary school										
Inverse of distance	0.257	1.011***	-0.035	0.075	0.033	0.347	0.925***	-0.104	-0.069	0.543***
Inverse of distance squared	-0.046	-0.882***	0.898	-0.008	-0.021	-0.308	-0.487***	0.164	0.022	-0.121***
N	1.754	2.889	2.777	3.918	4.158	4.804	3.017	4.512	7.780	3.541
Adjusted R squared	0.134	0.122	0.091	0.099	0.080	0.123	0.089	0.122	0.094	0.094
Complete primary school to high school graduates without college degree										
Inverse of distance	0.253	0.225	0.393	0.371***	0.146**	0.291	0.006	-0.977***	0.036	0.184**
Inverse of distance squared	-0.105	-0.033	0.083	-0.052***	-0.047	-0.451*	-0.050	0.889***	-0.002	-0.039*
N	3.015	3.979	4.187	4.091	8.071	4.749	6.550	6.041	13.138	6.989
Adjusted R squared	0.320	0.318	0.202	0.274	0.230	0.245	0.198	0.264	0.216	0.181
College degree										
Inverse of distance	1.047***	0.413	2.770***	0.751***	-0.076	-1.131**	0.018	-0.720	0.683***	0.059
Inverse of distance squared	-0.688***	-0.390	-2.733	-0.105***	0.040	0.436	-0.194	0.659	-0.195***	-0.006
N	790	868	1.157	1.059	3.252	1.275	1.113	1.503	3.969	1.382
Adjusted R squared	0.299	0.279	0.203	0.289	0.279	0.297	0.238	0.262	0.281	0.214

	Belém - PA	Goiânia - GO	Curitiba - PR	Fortaleza - CE	Recife - PE	Salvador - BA	Porto Alegre - RS	Belo Horizonte - MG	Rio de Janeiro - RJ	São Paulo - SP
All individuals										
Inverse of distance	0.450***	1.441***	1.962***	-0.150***	0.460***	-0.042	0.460***	1.832***	0.413***	1.688***
Inverse of distance squared	-0.124***	-0.784***	-1.620***	0.034**	-0.205***	0.009	-0.622***	-2.332***	-0.529***	-1.306***
N	15.523	16.951	32.523	27.034	33.852	27.923	42.000	48.518	83.302	154.584
Adjusted R squared	0.374	0.367	0.393	0.407	0.407	0.409	0.424	0.423	0.398	0.372
Up to incomplete primary school										
Inverse of distance	0.486***	0.996***	0.938***	0.124*	0.020	0.240***	0.399**	1.239***	0.280***	1.418***
Inverse of distance squared	-0.227***	0.138	-0.522	-0.040*	0.040	-0.118***	-0.297	-1.588***	-0.361***	-0.933***
N	4.933	6.284	10.494	9.662	11.485	8.451	13.073	17.989	22.455	45.652
Adjusted R squared	0.077	0.073	0.092	0.076	0.093	0.084	0.092	0.081	0.071	0.082
Complete primary school to high school graduates without college degree										
Inverse of distance	0.335***	1.784***	1.709***	-0.074	0.372***	-0.130**	0.453***	1.829***	0.772***	1.925***
Inverse of distance squared	-0.070*	-1.444***	-1.208***	0.006	-0.181***	0.056*	-0.609***	-2.203***	-0.882***	-1.539***
N	8.728	8.284	16.737	14.691	18.418	15.722	23.617	24.277	45.919	80.089
Adjusted R squared	0.189	0.221	0.196	0.212	0.202	0.211	0.221	0.218	0.183	0.183
College degree										
Inverse of distance	0.717***	0.928***	2.673***	-1.758***	1.176***	-0.419**	0.519*	1.947***	-0.579***	1.162***
Inverse of distance squared	-0.216***	-0.270	-2.514***	0.537***	-0.597***	0.097	-1.079**	-2.649***	-0.254	-0.889***
N	1.862	2.383	5.292	2.681	3.949	3.750	5.310	6.252	14.928	28.843
Adjusted R squared	0.255	0.258	0.262	0.278	0.252	0.236	0.228	0.260	0.227	0.206

Controls: age, age squared, color or race, schooling level (when applicable), household head, with children up to 15 years old, married, sector of activity, occupation, existence of a formal contract. Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Only male individuals aged 25 to 64 years old living within a distance of 30km from the centre are considered in the analysis. Sampling weights are taken into account with Stata command *pweight*. Complete tables are available under request to the authors.

Source: Authors' calculations.

Table 5. OLS Regressions of the Logarithm of the Hourly Wage

(for all individuals and by education group)

	Macapá - AP	Aracaju - SE	Vale do Rio Cuiabá - MT	Maceió - AL	Florianópolis - SC	João Pessoa - PB	Grande São Luís - MA	Natal - RN	Grande Vitória - ES	Manaus - AM
All individuals										
Workers commuting 6' to 30'	-0.093***	0.002	-0.038	-0.029	-0.008	0.021	-0.013	-0.014	-0.027	0.029
Workers commuting more than 30' to 1 hour	-0.100**	-0.058	-0.137***	-0.017	-0.040*	-0.015	-0.022	-0.095***	-0.075***	-0.042
Workers commuting more than 1 hour to 2 hours	-0.194***	-0.069	-0.216***	-0.085**	-0.098***	-0.043	-0.106**	-0.109***	-0.153***	-0.121***
Workers commuting more than 2 hours	0.086	0.121	-0.046	0.007	0.081	0.002	-0.048	0.078	-0.069*	-0.039
N	5.559	7.736	8.121	9.068	15.481	10.828	10.680	12.056	24.887	11.912
Adjusted R squared	0.429	0.461	0.366	0.446	0.418	0.442	0.356	0.458	0.433	0.340
Up to incomplete primary school										
Workers commuting 6' to 30'	-0.035	0.018	0.029	0.008	0.001	0.048	-0.028	-0.035	-0.095***	0.045
Workers commuting more than 30' to 1 hour	-0.017	0.015	-0.033	0.050	0.033	0.084	0.008	-0.023	-0.083**	0.048
Workers commuting more than 1 hour to 2 hours	-0.089	0.017	-0.129*	0.038	0.032	0.048	-0.054	-0.013	-0.125***	-0.032
Workers commuting more than 2 hours	0.062	0.016	-0.085	0.034	-0.136	-0.003	-0.038	-0.063	-0.054	-0.018
N	1.754	2.889	2.777	3.918	4.158	4.804	3.017	4.512	7.780	3.541
Adjusted R squared	0.130	0.114	0.090	0.097	0.080	0.123	0.079	0.122	0.096	0.089
Complete primary school to high school graduates without college degree										
Workers commuting 6' to 30'	-0.109**	-0.016	-0.056	-0.056	-0.016	-0.018	-0.029	-0.002	0.004	-0.013
Workers commuting more than 30' to 1 hour	-0.084	-0.110*	-0.176***	-0.078	-0.042	-0.105**	-0.014	-0.083**	-0.044	-0.119**
Workers commuting more than 1 hour to 2 hours	-0.214***	-0.163**	-0.211***	-0.192***	-0.096**	-0.113*	-0.121**	-0.162***	-0.118***	-0.172***
Workers commuting more than 2 hours	0.009	0.069	0.153	0.039	0.069	0.080	-0.022	0.168	-0.041	-0.036
N	3.015	3.979	4.187	4.091	8.071	4.749	6.550	6.041	13.138	6.989
Adjusted R squared	0.320	0.320	0.206	0.271	0.230	0.246	0.199	0.262	0.219	0.186
College degree										
Workers commuting 6' to 30'	-0.171**	0.099	-0.058	0.041	-0.020	-0.051	0.063	-0.053	-0.059	0.143
Workers commuting more than 30' to 1 hour	-0.367***	0.057	-0.186	0.087	-0.116**	-0.115	-0.129	-0.359***	-0.189***	0.058
Workers commuting more than 1 hour to 2 hours	-0.452**	0.028	-0.293	-0.037	-0.286***	-0.252	-0.192	-0.305**	-0.373***	-0.217*
Workers commuting more than 2 hours	0.104	0.579	-0.259	0.181	0.444**	-0.232	-0.128	0.218	-0.187	0.004
N	790	868	1.157	1.059	3.252	1.275	1.113	1.503	3.969	1.382
Adjusted R squared	0.301	0.279	0.181	0.263	0.287	0.285	0.241	0.281	0.287	0.222

	Belém - PA	Goiânia - GO	Curitiba - PR	Fortaleza - CE	Recife - PE	Salvador - BA	Porto Alegre - RS	Belo Horizonte - MG	Rio de Janeiro - RJ	São Paulo - SP
All individuals										
Workers commuting 6' to 30'	-0.044	-0.018	0.011	-0.013	-0.016	0.040	0.005	-0.013	-0.011	-0.018
Workers commuting more than 30' to 1 hour	-0.066**	-0.089***	-0.033*	-0.024	0.010	0.051**	-0.009	-0.048***	-0.002	-0.014
Workers commuting more than 1 hour to 2 hours	-0.132***	-0.193***	-0.123***	-0.112***	-0.051**	0.042	-0.044**	-0.125***	-0.031**	-0.067***
Workers commuting more than 2 hours	-0.015	-0.050	-0.102***	-0.086*	-0.022	0.085**	-0.062	-0.134***	-0.049**	-0.095***
N	15.523	16.951	32.523	27.034	33.852	27.923	42.000	48.518	83.302	154.584
Adjusted R squared	0.369	0.355	0.379	0.408	0.406	0.409	0.424	0.419	0.397	0.367
Up to incomplete primary school										
Workers commuting 6' to 30'	-0.001	-0.005	0.006	0.031	-0.050	0.020	-0.037	-0.068**	-0.082***	-0.046**
Workers commuting more than 30' to 1 hour	-0.021	-0.028	0.014	0.091***	0.001	0.067	0.004	-0.035	-0.025	-0.012
Workers commuting more than 1 hour to 2 hours	-0.106*	-0.122**	-0.018	0.038	-0.026	0.022	-0.028	-0.091***	-0.030	-0.041**
Workers commuting more than 2 hours	-0.077	0.017	-0.119**	-0.083	-0.063	0.091	-0.110**	-0.092**	0.005	-0.047**
N	4.933	6.284	10.494	9.662	11.485	8.451	13.073	17.989	22.455	45.652
Adjusted R squared	0.074	0.062	0.088	0.078	0.094	0.084	0.092	0.078	0.072	0.077
Complete primary school to high school graduates without college degree										
Workers commuting 6' to 30'	-0.061	-0.017	-0.032	-0.032	-0.010	0.018	0.004	-0.010	-0.017	-0.022
Workers commuting more than 30' to 1 hour	-0.049	-0.091**	-0.065***	-0.052*	0.023	0.031	-0.034	-0.058**	0.002	-0.030*
Workers commuting more than 1 hour to 2 hours	-0.095**	-0.239***	-0.176***	-0.143***	-0.040	0.038	-0.053**	-0.144***	-0.032	-0.081***
Workers commuting more than 2 hours	0.045	-0.105	-0.137**	-0.034	0.046	0.055	-0.032	-0.182***	-0.075***	-0.110***
N	8.728	8.284	16.737	14.691	18.418	15.722	23.617	24.277	45.919	80.089
Adjusted R squared	0.184	0.210	0.180	0.214	0.201	0.211	0.222	0.212	0.181	0.175
College degree										
Workers commuting 6' to 30'	-0.054	-0.060	0.128**	-0.137	0.072	0.150*	0.078	0.064	0.108**	0.022
Workers commuting more than 30' to 1 hour	-0.223**	-0.227***	-0.003	-0.289***	0.060	0.052	0.054	-0.020	0.025	0.026
Workers commuting more than 1 hour to 2 hours	-0.360***	-0.178	-0.249***	-0.612***	-0.086	0.058	-0.067	-0.131**	-0.011	-0.053*
Workers commuting more than 2 hours	-0.061	-0.135	0.323**	-0.323	-0.162	0.173	0.034	0.007	-0.049	-0.162***
N	1.862	2.383	5.292	2.681	3.949	3.750	5.310	6.252	14.928	28.843
Adjusted R squared	0.247	0.240	0.241	0.270	0.245	0.236	0.229	0.257	0.228	0.204

Controls: constant, age, age squared, color or race, schooling level (when applicable), household head, with children up to 15 years old, married, sector of activity, occupation, existence of a formal contract. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. Only male individuals aged 25 to 64 years old living within a distance of 30km from the centre are considered in the analysis. Sampling weights are taken into account with Stata command *pweight*. Complete tables are available under request to the authors.

Source: Authors' calculations.

In any case, Table 5 shows that the negative effect of commuting time on wages is significant for workers commuting for 30 minutes or more, and is higher the longer the time spent in this activity. For low-skilled workers in smaller metropolitan areas, wages are not significantly correlated to this measure of spatial mismatch. Moreover, for most metropolitan areas, workers who commute for two hours or more do not see any significant effect on their wages, which may result from the fact that there are only a few workers belonging to this group, and no clear wage pattern.

The second set of results refers to the probability of being unemployed. Coefficients are presented as odds-ratios, with values greater than one indicating a positive effect of the variable of interest on the probability of unemployment. Tables 6 and 7 present the estimated coefficients related to specific distance measures. Metropolitan areas are ranked from left to right according to the size of their labour market.

There is an indication in Table 6 that the probability of unemployment is not significantly correlated with the inverse distance to the centre. This result is consistent for most metropolitan areas, and there is no specific pattern for groups with different levels of schooling. The same result is found when distance to jobs is measured by the time spent by workers in the neighbourhood commuting from home to work (Table 7). Once again, for most metropolitan areas this relationship is not significant, and it does not show any pattern regarding education level, labour market size, or the sign of the correlation itself in cases when it is in fact significant.

A few aspects can be highlighted in relation to these results. On the one hand, unemployment levels may vary throughout the city in an irregular way, with no specific pattern in either monocentric or multicentric cities. In a sense, this conclusion in the Brazilian case matches part of the literature, which finds no regular pattern for the spatial distribution of the unemployment rate.

However, the conclusion goes against recent theoretical predictions that distance to jobs can affect the probability that individuals belonging to low-skilled minorities find a position. If these theoretical predictions are valid, it might be that there are methodological issues driving this unexpected result. First, distance is not measured in relation to an individual, but relates only to his or her neighbourhood. In addition, we do not take into account the location of job offers and existing jobs. Our database locates individuals by their place of residence. Therefore, there may be difficulties in correctly identifying the centres in the city and in calculating the relative location of each potential worker. Moreover, when distance is measured as the commuting time for workers in the neighbourhood, this may not be the same as the commuting time a potential worker would spend if he or she were in work.

Table 6. Logit Model for the Probability of Being Unemployed (regressions with all individuals and by education groups)

	Macapá - AP	Aracaju - SE	Vale do Rio Cuiabá - MT	Maceió - AL	Florianópolis - SC	João Pessoa - PB	Grande São Luís - MA	Natal - RN	Grande Vitória - ES	Manaus - AM
All individuals										
Inverse of distance	0.048**	0.664	-0.091	0.293	0.327	0.212	0.507	0.196*	3.722	0.322
Inverse of distance squared	1.624	1.360	1.752.896	1.086	0.979	3.338	0.593*	0.331	0.776**	0.907
N	3.300	4.343	4.385	4.464	8.357	5.079	7.122	6.495	13.860	7.583
Pseudo R squared	0.063	0.047	0.039	0.057	0.062	0.067	0.061	0.050	0.032	0.034
Up to incomplete primary school										
Inverse of distance	0.143	0.319	0.138	0.783	0.601	0.949	1.420	2.022	0.450	0.577
Inverse of distance squared	5.020*	5.173	2.102	1.024	0.333	1.625	0.735	0.368	1.112	0.991
N	1.917	3.223	2.952	4.448	4.320	5.389	3.291	5.027	8.268	3.916
Pseudo R squared	0.025	0.048	0.018	0.024	0.057	0.035	0.030	0.037	0.026	0.017
Complete primary school to high school graduates without college degree										
Inverse of distance	0.553	0.929	0.014	0.544	1.703	0.683	2.504*	1.423	2.401**	1.150
Inverse of distance squared	1.624	1.360	1.752.896	1.086	0.979	3.338	0.593*	0.331	0.776**	0.907
N	3.300	4.343	4.385	4.464	8.357	5.079	7.122	6.495	13.860	7.583
Pseudo R squared	0.063	0.047	0.039	0.057	0.062	0.067	0.061	0.050	0.032	0.034
Complete college										
Inverse of distance	0.045	50.401	44.300.167	0.984	0.187	17518.031***	95.374	126.576	2.558	0.610
Inverse of distance squared	12.062	0.140	0.000	0.913	2.021	0.000***	0.006	0.018	0.710	1.083
N	817	893	1.188	1.108	3.332	1.314	1.153	1.564	4.103	1.434
Pseudo R squared	0.133	0.247	0.109	0.156	0.064	0.172	0.169	0.131	0.083	0.085

	Belém - PA	Goiânia - GO	Curitiba - PR	Fortaleza - CE	Recife - PE	Salvador - BA	Porto Alegre - RS	Belo Horizonte - MG	Rio de Janeiro - RJ	São Paulo - SP
All individuals										
Inverse of distance	0.869	0.274	1.508	8.937*	0.545	0.503	0.360	0.487	1.264	0.679
Inverse of distance squared	0.928	8.401	0.170	1.020	1.859***	1.319**	3.314	0.171	1.260	2.041
N	9.494	8.604	17.310	15.623	20.350	17.292	24.572	25.418	48.893	85.450
Pseudo R squared	0.038	0.032	0.026	0.050	0.053	0.048	0.022	0.031	0.042	0.029
Up to incomplete primary school										
Inverse of distance	0.975	0.399	0.054	0.835	0.421**	0.423**	1.271	1.612	0.415	3.628**
Inverse of distance squared	0.788	0.744	362.490*	1.104	1.559**	1.528**	0.101	0.302	1.378	0.660
N	5.409	6.579	10.862	10.416	13.207	9.678	13.696	18.924	24.195	49.331
Pseudo R squared	0.020	0.030	0.023	0.027	0.027	0.023	0.022	0.023	0.018	0.016
Complete primary school to high school graduates without college degree										
Inverse of distance	1.166	0.400	8.058	1.023	0.252***	0.554**	0.710	3.538	0.667	0.409**
Inverse of distance squared	0.928	8.401	0.170	1.020	1.859***	1.319**	3.314	0.171	1.260	2.041
N	9.494	8.604	17.310	15.623	20.350	17.292	24.572	25.418	48.893	85.450
Pseudo R squared	0.038	0.032	0.026	0.050	0.053	0.048	0.022	0.031	0.042	0.029
Complete college										
Inverse of distance	0.785	2.935	7.154	0.798	1.496	5.741	0.203	0.808	2.261	1.597
Inverse of distance squared	1.050	0.165	0.005**	1.282	0.955	0.565	4.592	2.097	1.035	0.365
N	1.935	2.443	5.422	2.782	4.112	3.903	5.454	6.411	15.443	29.903
Pseudo R squared	0.059	0.054	0.045	0.103	0.090	0.078	0.024	0.028	0.057	0.028

Controls: age, age squared, color or race, schooling level (when applicable), household head, with children up to 15 years old, married. Coefficients are presented as odds-ratios. Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Only male individuals aged 25 to 64 years old living within a distance of 30km from the centre are considered in the analysis. Sampling weights are taken into account with Stata command *pweight*. Complete tables are available under request to the authors.
Source: Authors' calculations.

Table 7. Logit Model for the Probability of Being Unemployed (regressions with all individuals and by education groups)

	Macapá - AP	Aracaju - SE	Vale do Rio Cuiabá - MT	Maceió - AL	Florianópolis - SC	João Pessoa - PB	Grande São Luís - MA	Natal - RN	Grande Vitória - ES	Manaus - AM
All individuals										
% workers commuting 6' to 30'	0.048**	0.664	-0.091	0.293	0.327	0.212	0.507	0.196*	3.722	0.322
% workers commuting more than 30' to 1 hour	0.105	0.288	2.219	0.175	0.049**	0.475	0.168**	0.111**	5.284	5.128
% workers commuting more than 1 hour	0.516	0.929	2.128*	1.205	0.428	1.267	0.723	0.790	1.715*	0.847
N	6.034	8.459	8.525	10.020	16.009	11.782	11.566	13.086	26.231	12.933
Pseudo R squared	0.056	0.063	0.040	0.053	0.054	0.064	0.061	0.054	0.035	0.037
Up to incomplete primary school										
% workers commuting 6' to 30'	0.011*	3.231	-0.161	1.304	0.004**	0.151	1.532	0.126	1.701	0.493
% workers commuting more than 30' to 1 hour	0.005*	0.995	5.118	1.424	0.021*	0.159	0.546	0.257	2.175	5.536
% workers commuting more than 1 hour	1.398	1.639	2.514	1.715	0.006***	0.898	1.071	0.705	1.634	1.028
N	1.917	3.223	2.952	4.448	4.320	5.389	3.291	5.027	8.268	3.916
Pseudo R squared	0.026	0.046	0.019	0.025	0.059	0.035	0.030	0.038	0.025	0.016
Complete primary school to high school graduates without college degree										
% workers commuting 6' to 30'	0.101	0.299	0.040	0.047**	2.798	0.799	0.291	0.155	13.582**	0.166
% workers commuting more than 30' to 1 hour	0.336	0.160	3.518	0.018**	0.078	3.474	0.081**	0.038**	14.542**	4.042
% workers commuting more than 1 hour	0.349	0.884	2.588	0.631	1.368	3.524	0.570**	0.711	2.230*	0.657
N	3.300	4.343	4.385	4.464	8.357	5.079	7.122	6.495	13.860	7.583
Pseudo R squared	0.064	0.047	0.039	0.058	0.067	0.067	0.063	0.051	0.032	0.036
Complete college										
% workers commuting 6' to 30'	0.000	0.012	-0.301	0.337	0.210	0.000	2.668	0.343	0.047	13.079
% workers commuting more than 30' to 1 hour	0.056	0.005	0.031	0.010	0.061	0.002	0.574	0.493	1.331	901.885
% workers commuting more than 1 hour	0.158	0.003**	0.240	26.935*	4.475	0.002	0.999	0.524	0.180	1.656
N	817	893	1.188	1.108	3.332	1.314	1.153	1.564	4.103	1.434
Pseudo R squared	0.139	0.260	0.102	0.177	0.064	0.162	0.164	0.128	0.086	0.086

	Belém - PA	Goiânia - GO	Curitiba - PR	Fortaleza - CE	Recife - PE	Salvador - BA	Porto Alegre - RS	Belo Horizonte - MG	Rio de Janeiro - RJ	São Paulo - SP
All individuals										
% workers commuting 6' to 30'	0.869	0.274	1.508	8.937*	0.545	0.503	0.360	0.487	1.264	0.679
% workers commuting more than 30' to 1 hour	0.357	1.030	1.296	5.723	0.982	0.264	0.433	0.901	0.909	0.771
% workers commuting more than 1 hour	2.357	0.756	1.576	4.325	1.370	1.047	0.376**	0.733	1.158	1.020
N	16.838	17.626	33.594	28.821	37.669	30.873	43.722	50.753	88.531	164.684
Pseudo R squared	0.039	0.032	0.026	0.046	0.057	0.051	0.024	0.031	0.042	0.032
Up to incomplete primary school										
% workers commuting 6' to 30'	36.757	0.210	0.816	2.237	0.273	1.333	1.986	0.278	0.935	0.628
% workers commuting more than 30' to 1 hour	5.896	0.698	0.868	0.353	0.609	0.358	1.593	1.120	0.696	0.779
% workers commuting more than 1 hour	132.388*	1.024	1.929	3.518	0.699	2.183	1.376	0.738	1.321	0.981
N	5.409	6.579	10.862	10.416	13.207	9.678	13.696	18.924	24.195	49.331
Pseudo R squared	0.022	0.033	0.022	0.028	0.027	0.023	0.022	0.024	0.019	0.016
Complete primary school to high school graduates without college degree										
% workers commuting 6' to 30'	0.102	0.496	2.746	113.524***	0.670	0.404	0.067**	0.358	1.048	0.902
% workers commuting more than 30' to 1 hour	0.074	1.371	2.788	110.358***	1.243	0.249	0.111**	0.396	0.948	0.873
% workers commuting more than 1 hour	0.223	0.741	1.232	19.355**	1.854	0.837	0.121***	0.526	1.049	1.094
N	9.494	8.604	17.310	15.623	20.350	17.292	24.572	25.418	48.893	85.450
Pseudo R squared	0.039	0.032	0.025	0.051	0.053	0.048	0.023	0.031	0.042	0.029
Complete college										
% workers commuting 6' to 30'	0.266	0.234	0.305	0.042	6.864	0.015	17.634	12.783	0.689	0.337
% workers commuting more than 30' to 1 hour	0.139	10.454	0.064	4.959	1.456	1.056	18.005	55.136	0.345	0.512
% workers commuting more than 1 hour	0.878	0.071**	3.154	0.004	7.570	0.148	2.771	2.117	0.523	0.915
N	1.935	2.443	5.422	2.782	4.112	3.903	5.454	6.411	15.443	29.903
Pseudo R squared	0.059	0.065	0.038	0.102	0.091	0.080	0.024	0.030	0.058	0.029

Controls: age, age squared, color or race, schooling level (when applicable), household head, with children up to 15 years old, married. Coefficients are presented as odds-ratios. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. Only male individuals aged 25 to 64 years old living within a distance of 30km from the centre are considered in the analysis. Sampling weights are taken into account with Stata command *pweight*. Complete tables are available under request to the authors.

Source: Authors' calculations.

5. Final remarks

There is significant spatial mismatch in the labour market in Brazilian metropolitan areas. The influence of spatial location and distance to jobs on labour market outcomes is stronger for larger urban areas, and wages are more strongly related to distance to jobs and to distance to the centre than unemployment rates are. In addition, the difference in the commuting time for poor and rich workers is larger in labour markets with 500,000 workers or more.

The literature on spatial mismatch suggests that this phenomenon is predominantly urban and that it is more relevant for low-skilled minorities in larger urban areas for whom congestion costs are relatively more important. In addition, these minorities may face more limitations in their social interactions, with a significant impact on their ability to find a better match in the job market.

In this paper, we have attempted to investigate whether this negative relationship between spatial mismatch and labour market outcomes is valid in Brazil after controlling for individual characteristics. Our conclusions indicate that there is no clear relation between two different measures of accessibility to jobs and the probability of being unemployed. However, for wages there is a clear correlation, which is stronger in larger metropolitan areas.

This is intended to be an exploratory work. In this sense, we have explored correlations between labour market outcomes and measures of accessibility to jobs for Brazilian metropolitan areas. Our results depend on strong identification hypotheses to avoid bias related to simultaneous location decisions of workers and firms within the city. If these conditions do not hold, our results may not represent a causal relationship, but will be meaningful in the sense of providing a better understanding of the conditional distribution of wages and the unemployment rate in the biggest metropolitan areas of Brazil.

The broader analysis of urban labour markets in Brazil provides an indication that there are relevant differences in the way workers and firms interact in space, and urban scale seems to be important to this relationship. Future work should investigate these issues more thoroughly.

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Appendix

Table A.1 Average Hourly Wage in each Weighting Area, 2010 (by the distance to the main business centre)

	Less than 2.5 km	2.5 km to less than 5 km	5 km to less than 10 km	10 km to less than 20 km	20 km to less than 30 km	30 km to less than 40 km	40 km to less than 50 km	50 km or more
Macapá - AP	R$ 13.39	R$ 10.16	R$ 9.97	R$ 7.61		R$ 8.47		R$ 7.32
Aracaju - SE	R$ 13.21	R$ 13.71	R$ 8.73	R$ 8.09				
Vale do Rio Cuiabá - MT	R$ 25.43	R$ 19.16	R$ 10.53	R$ 7.31	R$ 8.03			R$ 6.57
Maceió - AL	R$ 16.02	R$ 9.79	R$ 8.46	R$ 6.70	R$ 5.04	R$ 4.90		
Florianópolis - SC	R$ 16.86	R$ 17.45	R$ 15.57	R$ 13.49	R$ 9.51	R$ 8.11	R$ 7.96	R$ 7.65
João Pessoa - PB	R$ 8.71	R$ 9.23	R$ 12.26	R$ 7.83	R$ 3.57	R$ 4.35	R$ 4.65	R$ 4.48
Grande São Luís - MA	R$ 10.86	R$ 11.30	R$ 13.53	R$ 9.10	R$ 4.68	R$ 4.25		
Natal - RN	R$ 6.92	R$ 5.79	R$ 13.81	R$ 11.66	R$ 4.59	R$ 5.42		
Grande Vitória - ES	R$ 11.26	R$ 22.14	R$ 13.72	R$ 8.21	R$ 7.84	R$ 6.71	R$ 10.52	R$ 9.99
Manaus - AM	R$ 11.69	R$ 18.03	R$ 11.20	R$ 10.07			R$ 4.58	R$ 6.68
Belém - PA	R$ 18.07	R$ 14.60	R$ 9.77	R$ 7.70	R$ 5.78	R$ 5.48	R$ 5.57	R$ 5.57
Goiânia - GO	R$ 31.60	R$ 17.21	R$ 12.91	R$ 8.63	R$ 6.19	R$ 7.22	R$ 7.21	R$ 9.00
Curitiba - PR	R$ 33.21	R$ 27.73	R$ 14.07	R$ 9.37	R$ 9.02	R$ 6.20	R$ 7.67	R$ 6.76
Fortaleza - CE	R$ 6.12	R$ 7.97	R$ 9.63	R$ 13.39	R$ 4.73	R$ 4.43	R$ 4.07	R$ 4.23
Salvador - BA	R$ 8.71	R$ 10.02	R$ 14.74	R$ 10.77	R$ 6.32	R$ 8.22	R$ 7.56	R$ 6.96
Recife - PE	R$ 12.18	R$ 15.88	R$ 10.57	R$ 8.70	R$ 6.53	R$ 4.52	R$ 6.38	R$ 6.38
Porto Alegre - RS	R$ 13.66	R$ 11.76	R$ 17.21	R$ 13.68	R$ 10.24	R$ 8.19	R$ 7.72	R$ 7.76
Belo Horizonte - MG	R$ 15.90	R$ 16.93	R$ 17.48	R$ 8.22	R$ 9.44	R$ 9.32	R$ 7.37	R$ 7.86
Rio de Janeiro - RJ	R$ 7.48	R$ 10.00	R$ 16.61	R$ 15.30	R$ 11.54	R$ 9.22	R$ 8.21	R$ 8.36
São Paulo - SP	R$ 30.01	R$ 22.61	R$ 25.06	R$ 15.62	R$ 10.59	R$ 9.48	R$ 12.74	R$ 12.18

Source: IBGE.

Table A.2 Average Individual Hourly Wage, 2010

(by commuting time from home to work)

	Up to 5 min.	6 min to half-hour	More than half-hour to 1 hour	More than 1 hour to 2 hours	More than 2 hours
Macapá - AP	R$ 10.96	R$ 11.04	R$ 8.32	R$ 7.39	R$ 12.36
Aracaju - SE	R$ 11.72	R$ 12.16	R$ 9.27	R$ 7.85	R$ 16.58
Vale do Rio Cuiabá - MT	R$ 18.88	R$ 14.47	R$ 11.81	R$ 7.75	R$ 15.31
Maceió - AL	R$ 7.96	R$ 10.01	R$ 9.21	R$ 6.87	R$ 11.14
Florianópolis - SC	R$ 13.52	R$ 14.19	R$ 13.48	R$ 11.10	R$ 15.77
João Pessoa - PB	R$ 9.56	R$ 10.97	R$ 7.99	R$ 6.56	R$ 6.93
Grande São Luís - MA	R$ 11.16	R$ 12.48	R$ 10.49	R$ 7.76	R$ 10.94
Natal - RN	R$ 10.81	R$ 11.35	R$ 7.66	R$ 6.61	R$ 11.45
Grande Vitória - ES	R$ 14.40	R$ 13.23	R$ 11.05	R$ 8.31	R$ 10.10
Manaus - AM	R$ 10.01	R$ 13.60	R$ 10.38	R$ 7.82	R$ 8.81
Belém - PA	R$ 12.18	R$ 11.49	R$ 10.70	R$ 7.99	R$ 12.06
Goiânia - GO	R$ 17.91	R$ 13.44	R$ 9.99	R$ 7.42	R$ 14.08
Curitiba - PR	R$ 14.54	R$ 15.32	R$ 12.55	R$ 8.54	R$ 9.45
Fortaleza - CE	R$ 10.04	R$ 10.45	R$ 8.80	R$ 6.33	R$ 8.43
Salvador - BA	R$ 9.45	R$ 10.85	R$ 11.23	R$ 11.08	R$ 13.33
Recife - PE	R$ 10.58	R$ 10.17	R$ 10.50	R$ 8.36	R$ 8.29
Porto Alegre - RS	R$ 12.27	R$ 13.50	R$ 11.55	R$ 9.82	R$ 9.97
Belo Horizonte - MG	R$ 13.18	R$ 13.02	R$ 11.55	R$ 9.25	R$ 9.05
Rio de Janeiro - RJ	R$ 14.22	R$ 12.87	R$ 13.29	R$ 12.77	R$ 10.46
São Paulo - SP	R$ 17.53	R$ 16.79	R$ 15.83	R$ 13.15	R$ 11.95

Source: IBGE.

Table A.3 Average Unemployment Rate in Each Weighting Area, 2010 (by the distance to the main business centre)

	Less than 2.5 km	2.5 km to less than 5 km	5 km to less than 10 km	10 km to less than 20 km	20 km to less than 30 km	30 km to less than 40 km	40 km to less than 50 km	50 km or more
Macapá - AP	7.2%	6.5%	7.5%	10.3%		12.4%		4.7%
Aracaju - SE	9.5%	6.5%	6.9%	9.0%				
Vale do Rio Cuiabá - MT	3.1%	3.5%	4.3%	5.0%	7.7%			8.9%
Maceió - AL	6.2%	7.0%	9.1%	7.7%	13.7%	11.8%		
Florianópolis - SC	3.1%	2.7%	2.6%	2.1%	3.3%	3.4%	1.1%	2.1%
João Pessoa - PB	8.6%	5.7%	5.4%	6.7%	8.3%	7.4%	13.9%	8.8%
Grande São Luís - MA	9.4%	7.4%	7.7%	7.0%	6.3%	4.1%		
Natal - RN	5.7%	8.2%	6.7%	6.4%	8.7%	7.1%		
Grande Vitória - ES	5.6%	4.4%	4.3%	5.4%	4.3%	4.9%	6.7%	5.9%
Manaus - AM	6.8%	6.2%	7.3%	7.6%			4.2%	6.9%
Belém - PA	7.5%	6.4%	5.7%	7.9%	6.6%	5.5%	9.8%	
Goiânia - GO	3.6%	3.3%	3.0%	3.6%	3.1%	4.1%	3.8%	5.8%
Curitiba - PR	2.8%	3.3%	3.0%	2.8%	3.5%	1.6%	2.2%	3.3%
Fortaleza - CE	7.0%	5.3%	5.2%	5.8%	6.2%	6.9%	5.7%	5.9%
Salvador - BA	8.5%	8.2%	8.2%	9.2%	11.0%	12.7%	15.3%	13.9%
Recife - PE	8.7%	7.1%	9.6%	9.7%	10.8%	11.6%	10.0%	
Porto Alegre - RS	4.0%	3.2%	3.7%	4.0%	3.7%	3.3%	2.7%	3.5%
Belo Horizonte - MG	3.8%	4.4%	4.1%	4.4%	3.9%	4.0%	4.0%	4.0%
Rio de Janeiro - RJ	4.7%	6.0%	5.1%	5.3%	6.2%	5.8%	6.7%	7.8%
São Paulo - SP	6.4%	5.1%	4.8%	5.9%	6.1%	5.8%	5.1%	4.1%

Source: IBGE.