

Access to opportunities and employment outcomes

Arthur Bazolli
IPEA

Filipe Cavalcanti
IPEA

Gabriel Ulyssea
UCL

Rafael H. M. Pereira
IPEA

Abstract

Where people live can importantly affect their social, economic and health outcomes. For example, different studies in North America and Europe have demonstrated that individuals' employment outcomes are shaped by the neighborhoods where they live because of how residential location determines higher or lower job search costs. Nonetheless, there is limited empirical evidence on the role of such neighborhood effects in shaping employment outcomes in cities in the Global South. Here we investigate how spatial access to job opportunities shape employment outcomes in Brazil's 18 largest metropolitan areas, comparing unemployment duration (spell) between individuals living in high- and low-accessibility areas. Using record-linkage between national administrative records on social welfare and labor market, we track between 2013 and 2019 the residential location and employment status of over 9 thousand socially vulnerable individuals who suffered a mass layoff event, where firms unexpectedly terminate a great portion of their workforce. Using survival models, we show that individuals living in areas with access to more jobs (4th quartile of employment accessibility) are on average 5.56 percentage points more likely to return to the labor market in the first quarter after a mass layoff than individuals living in low-accessibility areas (1st quartile), but the magnitude of this difference fades over time. We also find these results vary considerably across cities, what suggests that differences in the spatial configuration of cities may importantly shape labor-market resilience. In urban areas between 3 and 6 million inhabitants, workers at the top quartile had persistently better re-employment rates than the bottom one, reaching a 24.4 percentage points advantage after two years. By showing that proximity to job opportunities sharply shortens unemployment spells for low-income workers, the study underscores the value of integrating transport and land use policies that raise job accessibility for vulnerable populations so that cities can cushion the shock of mass layoffs and foster quicker, more equitable labor-market recovery.

Keywords: urban accessibility, local labor markets, unemployment

JEL codes: J63, J64, R23

Resumo

O local de moradia pode afetar significativamente o desenvolvimento social, econômico e de saúde das pessoas. Por exemplo, diferentes estudos na América do Norte e na Europa demonstraram que os resultados de emprego dos indivíduos são moldados pelos bairros onde vivem, devido à forma como a localização residencial determina custos mais altos ou mais baixos na procura de emprego. No entanto, há poucas evidências empíricas sobre o papel desses efeitos do bairro na formação dos resultados de emprego nas cidades do Sul Global. Aqui, investigamos como o acesso espacial a oportunidades de emprego influencia os resultados de emprego nas 18 maiores áreas metropolitanas do Brasil, comparando o tempo no desemprego entre indivíduos que vivem em áreas de alta e baixa acessibilidade. Cruzando registros administrativos nacionais de assistência social e mercado de trabalho, acompanhamos entre

2013 e 2019 a localização residencial e a situação profissional de mais de 9 mil indivíduos socialmente vulneráveis que sofreram uma demissão em massa, em que as empresas demitiram inesperadamente grande parte de sua força de trabalho. Usando modelos de sobrevivência, mostramos que indivíduos que vivem em áreas com melhor acesso a empregos (4º quartil de acessibilidade) têm, em média, 5,56 pontos percentuais a mais de chance de retornar ao mercado de trabalho no primeiro trimestre após uma demissão em massa do que indivíduos que vivem em áreas de baixa acessibilidade (1º quartil), mas a magnitude dessa diferença diminui com o tempo. Também descobrimos que esses resultados variam consideravelmente entre as cidades, o que sugere que as diferenças na configuração espacial das cidades podem moldar de forma importante a resiliência do mercado de trabalho. Em áreas urbanas entre 3 e 6 milhões de habitantes, os trabalhadores do quartil superior tiveram taxas de reemprego consistentemente melhores do que os do quartil inferior, alcançando uma vantagem de 24,4 pontos percentuais após dois anos. Ao mostrar que a proximidade das oportunidades de emprego reduz drasticamente os períodos de desemprego para os trabalhadores de baixa renda, o estudo ressalta a importância de integrar políticas de transporte e uso do solo que aumentem a acessibilidade ao emprego para as populações vulneráveis, de modo que as cidades possam amortecer o choque das demissões em massa e promover uma recuperação mais rápida e equitativa do mercado de trabalho.

Palavras-chave: acessibilidade urbana, mercados de trabalho locais, desemprego

Área de submissão: 7– Questões urbanas e metrópoles

1 Introduction

Where a worker lives within a metropolitan area can expand or limit their spatial access to jobs, shaping not only earnings trajectories (Knudsen, Hjorth e Pilegaard, 2022) but also broader welfare outcomes such as education (Chetty, Hendren e Katz, 2016) and social mobility (Chetty e Hendren, 2018; Connor e Storper, 2020). A vast literature in urban and labor economics—largely grounded in North American and European experience—has demonstrated that residential location influences job-search costs, the quality of job matches, and ultimately the duration of unemployment spells (Abrahams e Mabli, 2024; Andersson *et al.*, 2018; Flemming, 2020; Korsu e Wenglenski, 2010; Rogers, 1997). Classic spatial-mismatch arguments (Gobillon, Selod e Zenou, 2007; Ihlanfeldt e Sjoquist, 1998; Kain, 1968) contend that spatial separation between disadvantaged workers and employment centers exacerbates joblessness by inflating search costs and thinning effective labor-demand pools. More recent work leverages fine-grained commute data, high-resolution accessibility metrics, and quasi-experimental designs to estimate causal pathways linking place to employment outcomes (Andersson *et al.*, 2018; Bastiaanssen, Johnson e Lucas, 2022, 2025). Yet despite their conceptual reach, these studies are concentrated in Global North settings with mature transit systems, comparatively stable labor regulations, and lower overall income inequality.

This paper addresses that gap by investigating whether and how spatial access to jobs influences post-layoff labor-market outcomes in Brazil's major metropolitan areas. Exploiting an administrative panel that links nationwide social-welfare registries (Cadastro Único) to formal labor-market records (RAIS), we follow more than 9 thousand socially vulnerable workers who experienced firm-level mass-layoff events between 2015 and 2019. These shocks provide a plausibly exogenous trigger for job search, allowing us to isolate the role of residential location

from firm-specific factors. We pair the individual panel with walking accessibility surfaces—computed via high-resolution walking times along road networks—to classify households into quartiles of employment access.

Using survival models that account for individual demographics, pre-layoff earnings, local labor demand, and local labor market characteristics, we find stark spatial differentials in re-employment speed. Workers in the top quartile of job accessibility are 5.56 percentage points more likely to regain employment within two and a half months of displacement than comparable workers in the bottom quartile. This advantage attenuates over time and becomes statistically indistinguishable, suggesting that accessibility primarily affects the intensive margin of early job search rather than longer-term labor-market attachment. Robustness checks—including alternative accessibility thresholds, competing-risk specifications—confirm the stability of our estimates.

Our work is related to a growing strand of literature that links local labor markets to employment outcomes but mostly focused on developed economies. Evidence from structural job search models and quasi-experiments (Agrawal, Janeba e Jahn, 2024; Andersson *et al.*, 2018; Flemming, 2020; Guglielminetti *et al.*, 2024; Moretti e Yi, 2024) suggest that commuting costs induce inefficiencies in the labor market, such that workers living in areas with few opportunities face higher challenges in finding jobs and may end up with worse-paying jobs that do not match their skills, especially as unemployment duration increases. In particular, Guglielminetti *et al.* (2024) found that as spell increases, Austrian workers in smaller towns tend to accept jobs in their home towns instead of commuting to larger cities with better opportunities, due to higher job search costs. Beyond providing unique evidence from large cities in an emerging economy after a near-exogenous event, we also contribute to the literature by improving identification on intra-urban accessibility, as our geocoded dataset allowed us to calculate detailed accessibility measures at the individual level instead of relying on approximations like linear distances to urban centroids.

The remainder of the paper proceeds as follows. Section 2 describes the data sources and methods used in the paper. Section 3 details the empirical strategy, including survival specifications and identification assumptions. Section 4 presents the main results and robustness analyses. Section 5 concludes the paper discussing policy implications of our findings for transport planning, active labor-market programs, and urban development.

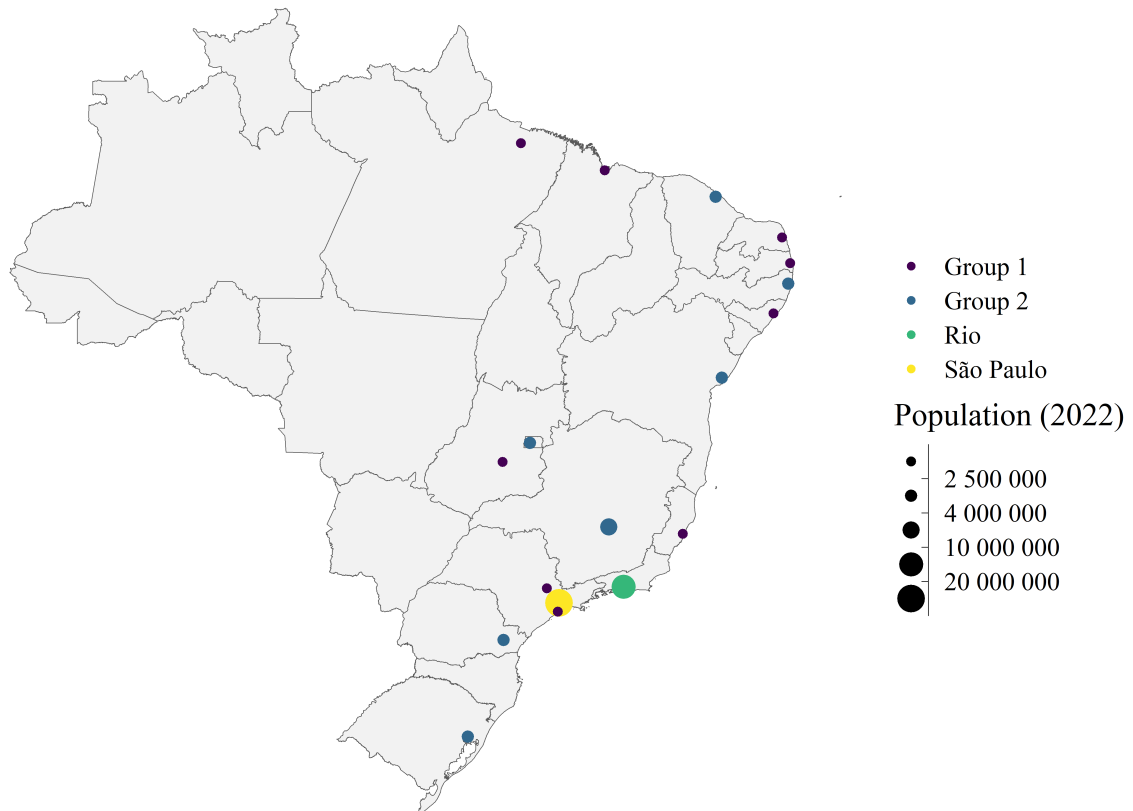
2 Data and methodology

The study focuses on Brazil's largest urban concentration areas. These areas are the equivalent of official urban functional regions created by the Brazilian Institute of Geography and Statistics (IBGE) with the aggregation of municipalities based on population ties due to work and school commuting trips, or due to contiguity between urbanized areas. Specifically, we focus on the 18 largest urban areas above one million inhabitants (Figure 1), which together encompassed 73 million people per the 2022 Census or a 36% of the Brazilian population. Here we will use as synonyms the terms “urban concentration”, “urban area”, and the name of the main city in each area.

We divided these urban areas into four groups based on their population. Nine of them are in Group 1 (population between one and 2.5 million inhabitants) and another seven in Group 2 (ranging from 3 to 5 million inhabitants). Since Rio de Janeiro is twice the size of Belo

Horizonte—the largest urban concentration in Group 2—and São Paulo is twice the size of Rio, they are not grouped.

Figure 1: Map of Brazil with the selected urban concentrations



Source: Elaborated by the authors.

1.1 Data sources and panel dataset

We build a rich panel data set that links nationwide formal labor-market records (RAIS) with social-welfare registries (Cadastro Único). RAIS is the Brazilian employer-employee dataset covering all formal work relationships in the country since 1985. This data provides detailed information on workers' economic sector, job location, income and education attainment. The data also includes information on the dates when workers are hired and dismissed. This allows us to determine which firms went through mass layoffs between 2014 and 2019, which led to the termination of 445 thousand workers in this period. We further add to our data information on workers' gender, age, and eventual death date using federal tax registry data (b-Cadastrados), which is a more reliable source of information on demographic characteristics than RAIS.

Of all these workers, 34% of them (150 thousand) were registered in *Cadastro Único* (CadÚnico), an official national registry of socially vulnerable households who are eligible for welfare programs. We focus on these workers present in CadÚnico for two key reasons. First, from a practical point of view, the CadÚnico data set is the most reliable data source on individuals' home addresses available in Brazil, since all households must update their registry every two years to remain eligible for social welfare programs. Second, by considering only the workers present in CadÚnico, we focus our analysis on a relatively less heterogenous

population with similar socioeconomic conditions. This allows us to better identify the impact of spatial accessibility by isolating income effects, since all individuals in the analyzed group fit roughly in the same socioeconomic level.

The result of this process is a panel dataset at the individual level tracking all workers that went through a mass layoff event between 2014 and 2017 in 18 urban areas. The data indicates for each worker the unemployment duration between the first time they go through a mass layoff event and when they eventually return to the labor market. Finally, we used the R package `{geocodebr}` (Pereira e Herszenhut, 2025) to geolocate the addresses of all firms in RAIS as well as the residential locations of workers from CadÚnico. This allowed us to calculate for each worker their spatial access to job opportunities (see section 2.3), which we separated in quartiles and kept the top and bottom ones. Because home and work location can be endogenous, we minimize this issue by considering only those workers who did not change residence after the date of mass layoff, which resulted in a final dataset with 9 thousand workers.

Table 1 below summarizes key statistics for our database, as well as the difference in means between the first and fourth accessibility quartiles.

Table 1: Balance table for accessibility quartiles

Variable	1st quart. Mean	1st quart. Std. dev.	4th quart. Mean	4th quart. Std. dev.	Difference in means	
Spell (months)	16.13	8.77	15.80	8.92	-0.33	
Woman = 1	0.68	0.47	0.75	0.43	0.07	***
Nonwhite = 1	0.11	0.31	0.12	0.32	0.01	+
Birth year	1979	10.16	1978	10.51	-0.60	*
High school degree	0.53	0.50	0.58	0.49	0.05	***
Bachelor's degree	0.02	0.15	0.06	0.23	0.03	***
Manual worker	0.26	0.44	0.15	0.35	-0.11	***
Retail worker	0.50	0.50	0.47	0.50	-0.03	**
Office worker	0.18	0.38	0.31	0.46	0.13	***
Technician	0.05	0.22	0.05	0.22	0.00	
Higher qualif.	0.01	0.12	0.03	0.16	0.01	***
Tenure (years)	2.50	2.93	2.59	3.15	0.09	
Wage/min wage	1.47	0.87	1.39	1.08	-0.08	***

Source: Elaborated by the authors.

Notes: “+” = significant at 10%, “*” = significant at 5%, “**” = significant at 1%, “***” = significant at 0,1%. Occupations according to the Brazilian official classification (CBO) were aggregated as follow: manual work (CBO 6–9); customer service and retail (CBO 5); office/administrative services (CBO 4); technicians (CBO 3); higher qualification (CBO 1–2). Wages are expressed as the monthly averages divided by the national minimum wage.

In short, the balance table indicates that on the average of the 18 urban areas, most of the covariates are statistically different at the 99% confidence level between quartiles, but the magnitude varies. About half the sample completed the basic educational cycle (up to high school) but did not pursue or finish a secondary course. Manual workers—which encompass maintenance and repair, manufacturing, and agriculture (although the last is scarce in those urban areas)—are more frequent in the first quartile, in opposition to office workers. This is consistent with stylized facts on the spatial distribution of jobs in the urban space, since the top quartile of the accessibility distribution is concentrated around business districts and the bottom

quartile mostly coincides with the urban fringes, where industrial jobs tend to locate (Glaeser e Kahn, 2004; Redding e Turner, 2015; White, 1999). The higher proportion of women in the sample stems from the fact that most CadÚnico registers are in the name of a household's woman, generally a mother, for the purposes of receiving Bolsa Família, the Brazilian conditional cash transfer linked to school enrollment.

1.2 Definition of mass layoff

There is a broad understanding in the literature that a mass layoff event occurs when a company terminates many workers at once (Andersson *et al.*, 2018; Britto, Pinotti e Sampaio, 2022; Celli, Cerqua e Pellegrini, 2023). Nonetheless, there is no definitive criteria on what constitutes a mass layoff. Here, we adopt similar criteria proposed in Britto, Pinotti, and Sampaio (2022). To be considered a mass layoff, at least a third of all workers must be dismissed from the firm in the same month, and no more than 20% of these terminations can happen by the worker's initiative. Because these criteria can be fragile for small firms, we opted to only consider mass layoff events in firms with 50 or more employees.

1.3 Spatial accessibility to jobs

Another key step in our methodology is to determine the level of spatial access to jobs from the residential location of each worker. To do this, the geolocated data of firms and workers' home locations were spatially aggregated over a hexagon grid using the hierarchical index H3 (Brodsky, 2020) at resolution 9. Each hexagon cell has an area of 0.11 km², covering a couple city blocks depending on local street layout. Next, we estimated travel time matrices between the centroids of H3 cells considering network distances along the road network and a walking speed of 3.6 km/h. We used walking as transportation mode as the second-best option because there is no public transit data available that covers the entire urban areas under study.

These walking time estimates were then used to calculate the number of jobs that can be reached from every hexagonal cell in each year. As a form of sensitivity analysis, we conduct the analysis considering various accessibility metrics, including a gravity measure, a cumulative accessibility measure and a competition-based accessibility metric.¹ For the sake of brevity, we only report here the results using a gravity-based accessibility metric using a logistic decay function. In this indicator, we calculate the total number of jobs accessible, but each job is weighted using logistic decay function so that jobs further away count less than jobs nearby.

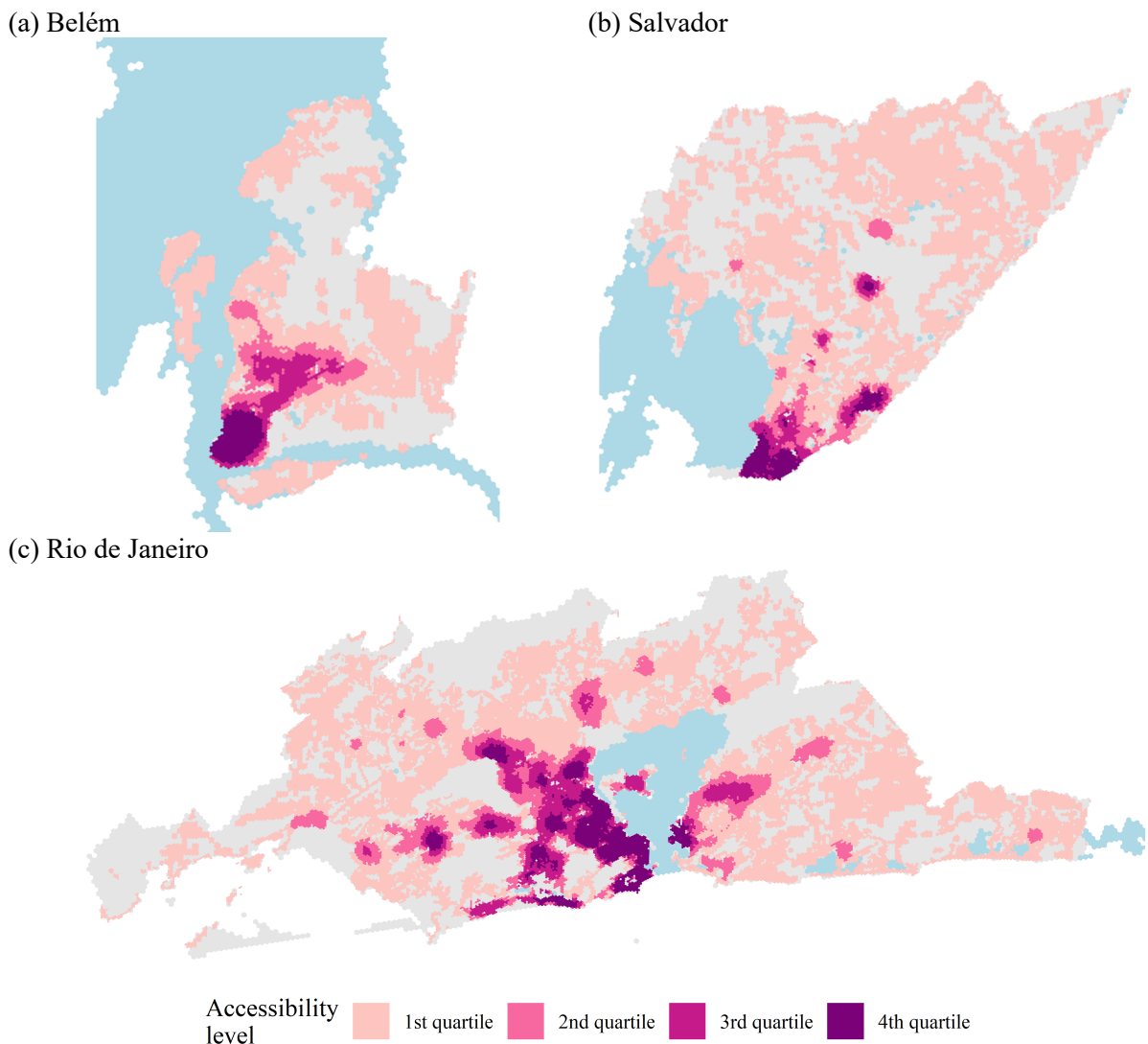
The final step was to calculate the quartile ranges of employment accessibility in each city and determine the quartile of each worker based on their hexagonal cell of residence. A detailed explanation of each accessibility metric is presented in Supplementary Information A.

Figure 2 below shows the map of three selected cities to illustrate the spatial distribution of accessibility quartiles. Even though these cities differ substantially in size—Belém (Group 1) has 1.9 million inhabitants, while Salvador (Group 2) has 3.3 million, and 11.8 million live in Rio de Janeiro—to some degree they have a common pattern: the bottom quartile coincides with the peripheral areas, whereas the top quartile consists mostly of the main city's central business district (CBD) and local centralities. But besides extent and level of density, city

¹ All metrics were calculate using the R package *{accessibility}* (Pereira e Herszenhut, 2024).

groups also differ in their urban structure. Group 1, despite consisting of relatively large-sized urban areas (they are all above one million inhabitants), has mostly monocentric cities such as Belém, in which almost no region matches the level of opportunities found near the CBD. Local centralities, in turn, play a bigger role in larger labor markets, e.g. in Salvador, where the cities of Lauro de Freitas and Camaçari also feature high-accessibility areas. In an even larger metropolis like Rio, multiple high-access islands are scattered around the urban core, such as Niterói across the Guanabara Bay and even the distant Campo Grande neighborhood in the West Zone. But since accessibility depends both on spatial distribution of jobs and people, this pattern also results from many individuals living far away from the dense urban core; indeed, local centralities are no way equivalent in size to the darker spots in central areas.

Figure 2: Accessibility maps for selected cities



Source: Elaborated by the authors.

Note: maps not to scale.

1.4 Survival analysis

To understand how spatial accessibility to jobs affects the odds of getting a job after a mass layoff, our main outcome measures unemployment duration (spell) after an individual is fired.

This is possible through survival analysis, a statistical approach used for time-to-event analysis (Collett, 2023). Fairly used in epidemiology, it is also applied in different topics in economics, e.g. school evasion (Gury, 2011; Saccaro, França e Jacinto, 2019), firm survival (Giovannetti, Ricchiuti e Velucchi, 2011), and (un)employment (Arrow, 1996; Bell *et al.*, 2024; Borges, 2022).

Among the different survival techniques available², we opted for the Cox proportional hazards model, a widely used approach that accounts for the impact of covariates. In the survival terminology, the analyzed event is often referred to as “death”, i.e., an individual dies if the event happens at a given time and is otherwise censored if it survives during the covered period. In our study, death happens when a worker returns to formal employment in up to 24 months following their layoff, whereas those that never return to employment (or that do so later than 24 months) are censored. Our interest lies in the hazard function, which expresses the probability of the event taking place in time t . Here, we will use the terms “death” and “employment” interchangeably, as well as “hazard” and “employment probability”.

A key assumption of the Cox model is that the death hazard is proportional for individuals of different categories regardless of time. In other words, white women laid off after two years in the same firm might have a different hazard rate than black men that worked for 13 years in their previous job, but this rate is the same along the 24-months window.

Mathematically, let $h_i(t)$ be the hazard rate function for individual i ,

$$h_i(t) = h_0(t) \exp(\boldsymbol{\beta} \mathbf{x}_i), \quad (1)$$

where $h_0(t)$ is the baseline hazard (employment probability) for any individual, \mathbf{x}_i is a matrix of covariates, and $\boldsymbol{\beta}$ is the matrix of coefficients. Our covariates matrix includes *woman*, a dummy for individuals registered as female in the federal tax registry (b-Cadastrós), *nonwhite*, which is one for individuals declared as any ethnicity other than white in RAIS, *age*, *rem_med_sm*, the average monthly wage as a multiple of that year’s national minimum wage, and a set of dummies for urban areas. We also included two different specifications: first, an overall model with all urban areas and split by accessibility level; second, city group \times access level pairs separately, such that we allow hazard rates to vary over time for these groups.

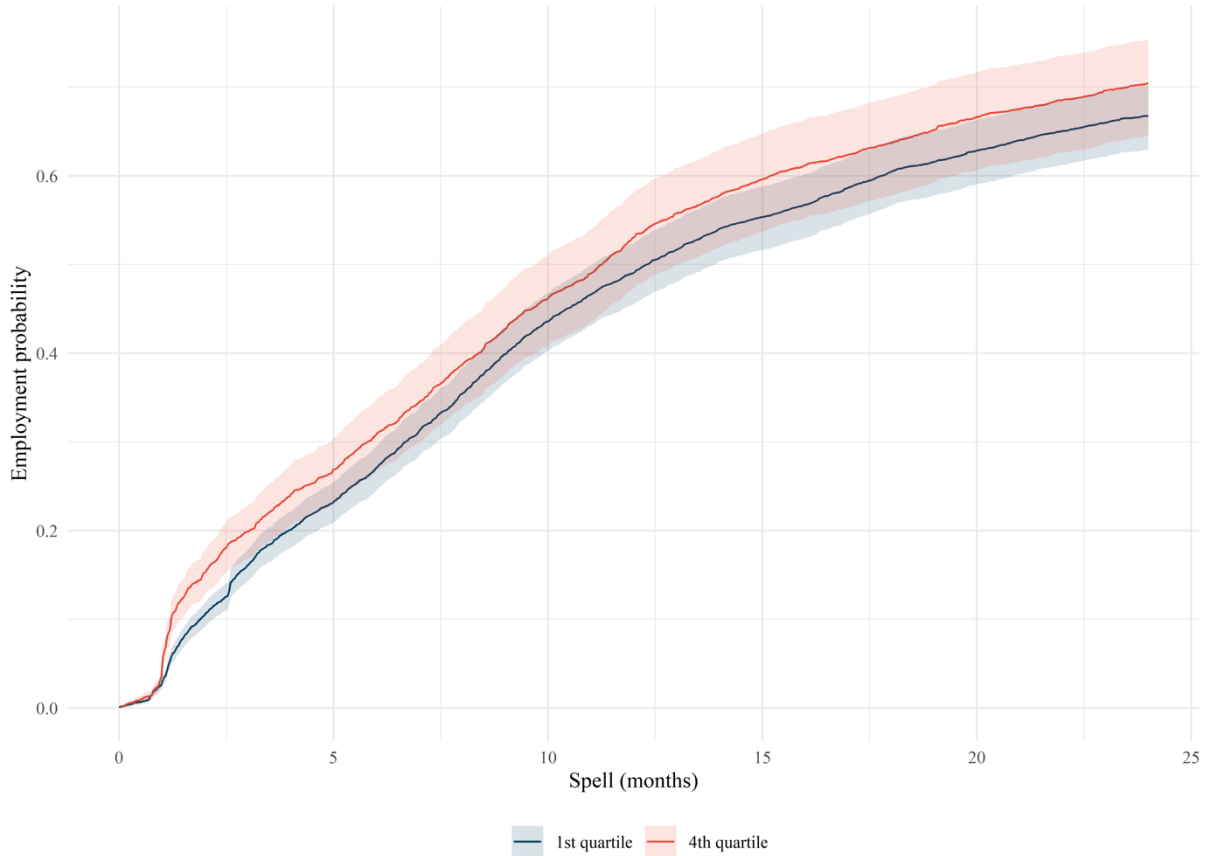
3 Results

Throughout this section, survival plots depict fitted cumulative re-employment rate for the top and bottom quartiles of the logistic accessibility index. Even when cities are aggregated, quartiles represent their own city value, e.g. the first quartile in group 2 includes individuals from the bottom accessibility level of both Belo Horizonte and Salvador, among others. We have also included the cox model’s coefficients and goodness-of-fit statistics, although causal interpretation cannot be inferred from covariates since their fit the purpose of adjusting the model to better isolate confounding factors from accessibility.

² See Hosmer, Lemeshow, and May (2008) and Collett (2023) for comprehensive literature on survival analysis.

Beginning from the aggregate level, the results for all cities in Figure 3 point out that throughout most of the time there is no significant difference between the 4th and 1st quartiles, even though the former stays on top of the latter for the entire period. Still, workers with better accessibility indeed had a head start in their job prospects: by the half of the second month, their employment rate was 5.56 percentage points greater than that of the first quartile (CI 4.22, 6.83).

Figure 3: Survival curves for employment probability, all cities combined



Source: elaborated by the authors.

Notes: Vertical axis corresponds to $1 - survival$; shadowed areas represent 95% confidence interval.

More than half of the laid off workers return to formal employment in the following 12 months. While the inclination of survival curves at that period suggest that those individuals would have reached full employment by the end of the second year, that was not the case; instead, re-employment starts to decline after workers have spent one year unemployed. Nevertheless, the employment rate reaches almost 70% on the 24th month.

Table 2: Cox proportional hazards model by quartile, all cities combined.

Term	1st quartile	4th quartile
woman	-0.321 *** (0.043)	-0.286 *** (0.057)
nonwhite	0.021 (0.064)	-0.081 (0.083)
age	-0.014 *** (0.002)	-0.017 *** (0.002)

Term	1st quartile	4th quartile
rem_med_sm	0.031 (0.020)	0.039 * (0.018)
muni_bel	-0.575 *** (0.147)	-0.594 *** (0.142)
muni_cam	-0.082 (0.082)	-0.340+ (0.203)
muni_slz	-0.614 *** (0.101)	-0.673 *** (0.121)
muni_ssz	-0.252 (0.196)	-2.341 * (1.003)
muni_vix	-0.460 *** (0.135)	0.310 (0.194)
muni_goi	-0.049 (0.136)	0.215 (0.238)
muni_jpa	-0.071 (0.157)	-0.665 + (0.360)
muni_mcz	-0.066 (0.305)	-0.599 + (0.310)
muni_nat	-0.639 *** (0.169)	-1.284 *** (0.384)
muni_bho	-0.092 (0.082)	-0.114 (0.121)
muni_bsb	-0.045 (0.082)	-0.093 (0.127)
muni_cur	0.178 + (0.099)	-0.078 (0.170)
muni_for	0.111 (0.079)	0.069 (0.097)
muni_poa	0.588 *** (0.099)	0.496 *** (0.144)
muni_rec	-0.337 *** (0.098)	-0.821 *** (0.144)
muni_sal	-0.821 *** (0.091)	-0.243 * (0.105)
muni_rio	-0.372 *** (0.075)	-0.257 ** (0.080)
Num.Obs.	5061	3024
AIC	43159.9	24875.6
BIC	43297.1	25001.9
RMSE	0.72	0.73

Source: Elaborated by the authors.

Notes: Standard errors in parentheses; “+” = significant at 10%, “*” = significant at 5%, “***” = significant at 1%, “****” = significant at 0,1%.

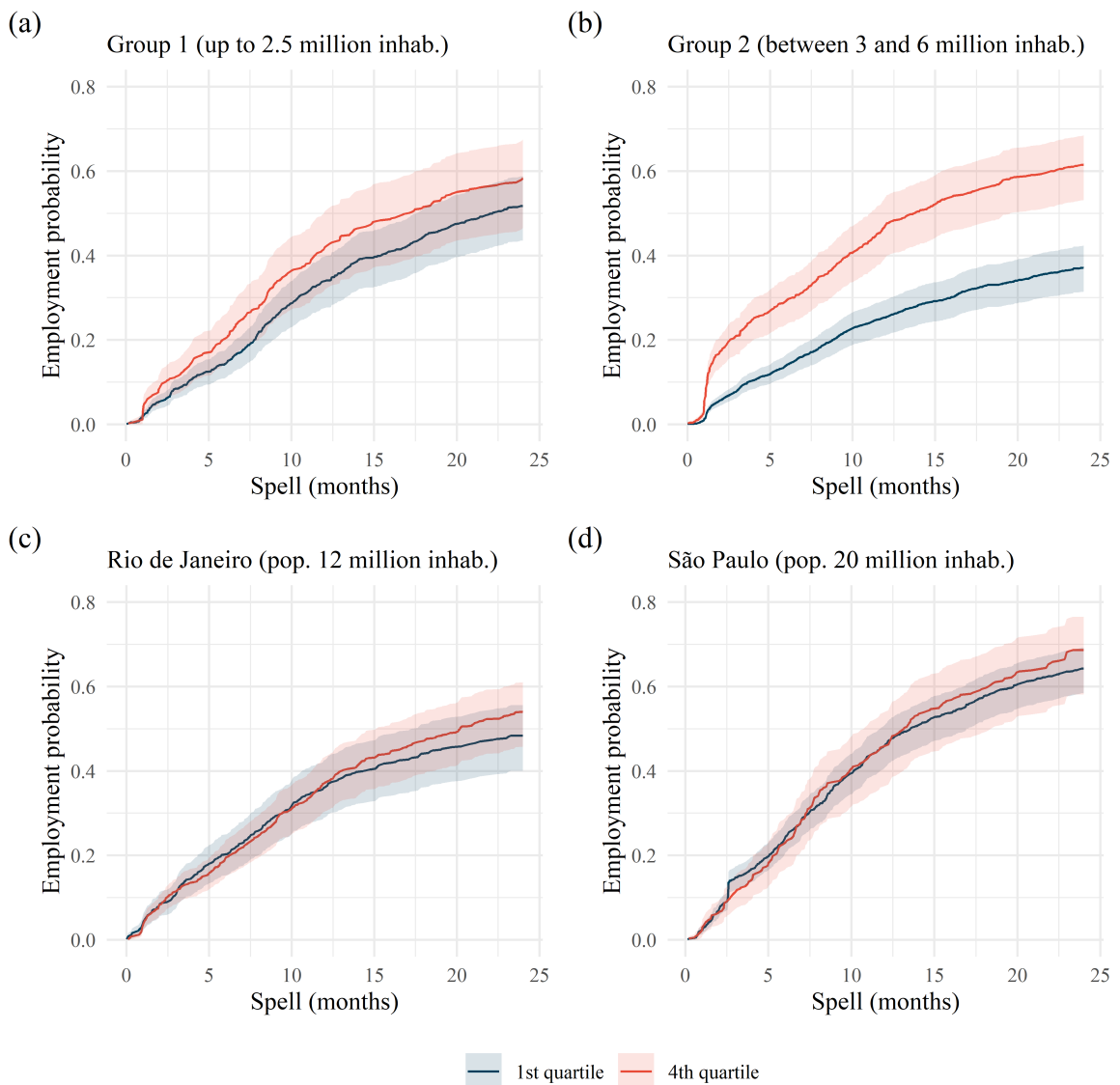
A greater degree of heterogeneity arises when looking closely at city groups, as Figure 4 reveals. The starkest difference is the distance between outcomes in the top and bottom quartiles of

Group 2: while the fourth quartile had similar results to its counterpart in Group 1, the first one performed worse than any other cohort, averaging at a re-employment rate as low as 37% after two years.

Inter-quartile differences in the average-sized urban areas in Group 1, although numerically and visually noticeable, are statistically irrelevant, probably due to its smaller sample size. Still, it comes nowhere close to the inequality seen in the bigger labor markets of Group 2. Rio and São Paulo, despite being two to three times larger than the biggest urban area in the second group, had consistently similar results for both accessibility levels.

City groups also vary on their degree of success in re-employing laid off workers. After two years, roughly 50% to 60% of individuals in Group 1 were re-employed, a slightly worse figure for Rio de Janeiro (48%-54%); Group 2, hence, is both worse than all the other groups—at the bottom—and in line with the best results of Group 1 and Rio, in its 4th quartile. Still, no group achieves better results than São Paulo, where employment reached roughly 65%-70%.

Figure 4: Survival curves for employment probability between city groups



Source: elaborated by the authors.

Notes: Vertical axis corresponds to $1 - survival$; shadowed areas represent 95% confidence interval.

Table 3: Cox proportional hazards model, city \times quantile groups

Term	Group 1		Group 2		Rio de Janeiro		São Paulo	
	1st quartile	4th quartile	1st quartile	4th quartile	1st quartile	4th quartile	1st quartile	4th quartile
woman	-0.598 *** (0.087)	-0.715 *** (0.140)	-0.303 *** (0.067)	-0.294 *** (0.087)	-0.231 + (0.138)	-0.076 (0.119)	-0.138 (0.087)	-0.087 (0.149)
nonwhite	0.230 (0.177)	-0.067 (0.250)	0.085 (0.098)	-0.138 (0.118)	0.311 (0.216)	0.137 (0.168)	-0.178+ (0.106)	-0.269 (0.212)
age	-0.020 *** (0.004)	-0.010 (0.007)	-0.007 * (0.003)	-0.009 * (0.004)	-0.025 *** (0.007)	-0.025 *** (0.005)	-0.016 *** (0.004)	-0.027 *** (0.007)
rem_med_sm	0.079 + (0.043)	0.034 (0.061)	0.009 (0.036)	0.051 (0.034)	0.027 (0.049)	0.026 (0.028)	0.053 (0.038)	0.138 * (0.062)
muni_bel	-0.020 (0.170)	0.055 (0.164)						
muni_cam	0.539 *** (0.120)	0.335 (0.218)						
muni_goi	0.536 *** (0.161)	0.847 *** (0.254)						
muni_jpa	0.444 * (0.181)	-0.085 (0.384)						
muni_mcz	0.385 (0.324)	0.074 (0.332)						
muni_nat	-0.059 (0.190)	-0.677 + (0.393)						
muni_ssz	0.330 (0.215)	-1.708 + (1.011)						
muni_vix	0.170 (0.160)	1.048 *** (0.213)						
muni_bho			0.741 *** (0.109)	0.121 (0.135)				

Term	Group 1		Group 2		Rio de Janeiro		São Paulo	
	1st quartile	4th quartile	1st quartile	4th quartile	1st quartile	4th quartile	1st quartile	4th quartile
muni_bsb			0.794 ***	0.119				
			(0.110)	(0.141)				
muni_cur			0.995 ***	0.127				
			(0.124)	(0.181)				
muni_for			0.946 ***	0.276 *				
			(0.108)	(0.116)				
muni_poa			1.401 ***	0.709 ***				
			(0.123)	(0.155)				
muni_rec			0.528 ***	-0.555 ***				
			(0.125)	(0.157)				
Num.Obs.	1255	589	2099	1225	553	832	1154	378
AIC	8103.0	3133.8	16193.4	9211.8	2964.9	5592.9	9154.4	2702.1
BIC	8164.6	3186.3	16249.9	9262.9	2982.2	5611.8	9174.6	2717.9
RMSE	0.69	0.68	0.73	0.75	0.66	0.72	0.77	0.80

Source: Elaborated by the authors.

Notes: Standard errors in parentheses; “+” = significant at 10%, “*” = significant at 5%, “**” = significant at 1%, “***” = significant at 0,1%.

4 Discussion

Our findings provide evidence that accessibility plays a significant role in shaping the speed of re-entry into the labor market following mass layoffs among low-income workers in Brazilian medium to large urban areas. At an aggregate level, individuals residing higher accessibility areas were more likely to return to formal employment within the first months after displacement. Nevertheless, when cities are separated by their size inter-quartile differences disappear in the biggest cohorts (over 10 million inhabitants), where survival curves follow closely, but also in the smaller group (less than 3 million), even though curves are more spaced and confidence intervals are large. It is in the middle group—labor markets with population between 3 and 6 million—that differences are more pronounced. High-accessibility workers have a headstart of around 15 percentage points already in their first month of unemployment, a difference that grows to almost 25 p.p. after two years.

Intuitively, workers in more compact cities are closer to job opportunities, and therefore the lack of statistical difference between top and bottom quartiles in Group 1 can indicate that accessibility is less of a barrier in those cities. Group 2, in turn, consists of larger metropolitan areas where less workers reside at walking distance from job opportunities, but in contrast with Rio and São Paulo, most of them have less developed mass transit networks that could increase the labor market pool attainable farther away from the urban core, in line with the spatial mismatch hypothesis. At the same time, the fact that São Paulo and Rio do not suffer from the same inequality gap found in Group 2 can be a consequence of

As a secondary result, we found that workers in larger cities also have better success in finding a new job, since the average employment of the better-off group in medium-sized cities (60%) is 5 percentage points below that of the worst group in São Paulo, the largest urban area in Latin America. This is in line with evidence from the U.S. (Moretti e Yi, 2024) and with the micro-foundations of agglomeration economies (Duranton e Puga, 2004), according to which the larger pool of job opportunities provided by larger labor markets means not only a bigger number of opportunities but also a greater match between firms and job-seekers.

A limitation of our methodology is that we cannot capture the higher accessibility provided by public transit, which we believe plays an important role in proportion to city size. The lack of public information on transit networks was a limiting factor, since data is mostly available for a handful of municipalities that do not cover the extent of a whole local labor market. As a future extension of this work, we will analyze a limited set of metropolitan areas for which there is complete information on transit networks. Additional contributions could be given by modelling spatial accessibility for different industries or occupations, to better assess the set of attainable opportunities based on worker skills.

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Supplementary information

A Accessibility metrics

We conducted the analysis considering three different accessibility metrics. The cumulative measure is the simplest one, where each opportunity accessible under a given cutoff assumes value one and the remainder assumes value zero. Mathematically,

$$A_{oT} = \sum_{d=1}^n P_d f(t_{od}), \quad (2)$$

where A_{oT} is the threshold cumulative accessibility of origin o in up to time T (60 minutes in our case), n is the number of destinations, P_d is the number of opportunities in destination d , and $f(\cdot)$ is zero if the travel time from the origin to the destination (t_{od}) is greater than T and one otherwise (Tomasiello *et al.*, 2023).

Thanks to its ease of use and interpretability, the cumulative measure is widely used in the accessibility literature, but has two main drawbacks: the crisp cutoff, which depends on an arbitrary decision, and the lack of consideration for the relative attractiveness of some opportunities regarding how close they are or how many other individuals can access them. The next two measures address these issues.

Gravity-based metrics, in turn, consider that closer opportunities matter more than those farther away, through a decay function in which travel costs are increasing with distance. It follows Equation (2) but with an impedance function instead of $f(t_{od})$. In particular, we use Bauer and Groneberg's (2016) logistic decay function,

$$CDF(d) = \frac{T}{1 + e^{\frac{(d - \text{median}) \cdot \pi}{SD \cdot \sqrt{3}}}} \quad (34)$$

where the cumulative distribution function $CDF(d)$, is the ratio between the asymptotic ceiling (T) and an exponential function depending on the median and the standard deviation (SD) of the CDF. The logistic is an s-shaped curve. Intuitively, the standard deviation determines how quickly farther opportunities become less attractive than closer ones.

Our third metric builds upon the second one and introduces a notion of competition. Intuitively, reaching 10 thousand jobs in a middle-sized city such as João Pessoa is not the same as reaching the same number of opportunities in São Paulo, the biggest metropolis in Latin America, since those opportunities are also available for a greater number of potential job seekers. In that sense, we use the spatial availability metric of Soukhov *et al.* (2023):

$$V_o = \sum_{d=1}^n P_d F_{od}^t, \quad (56)$$

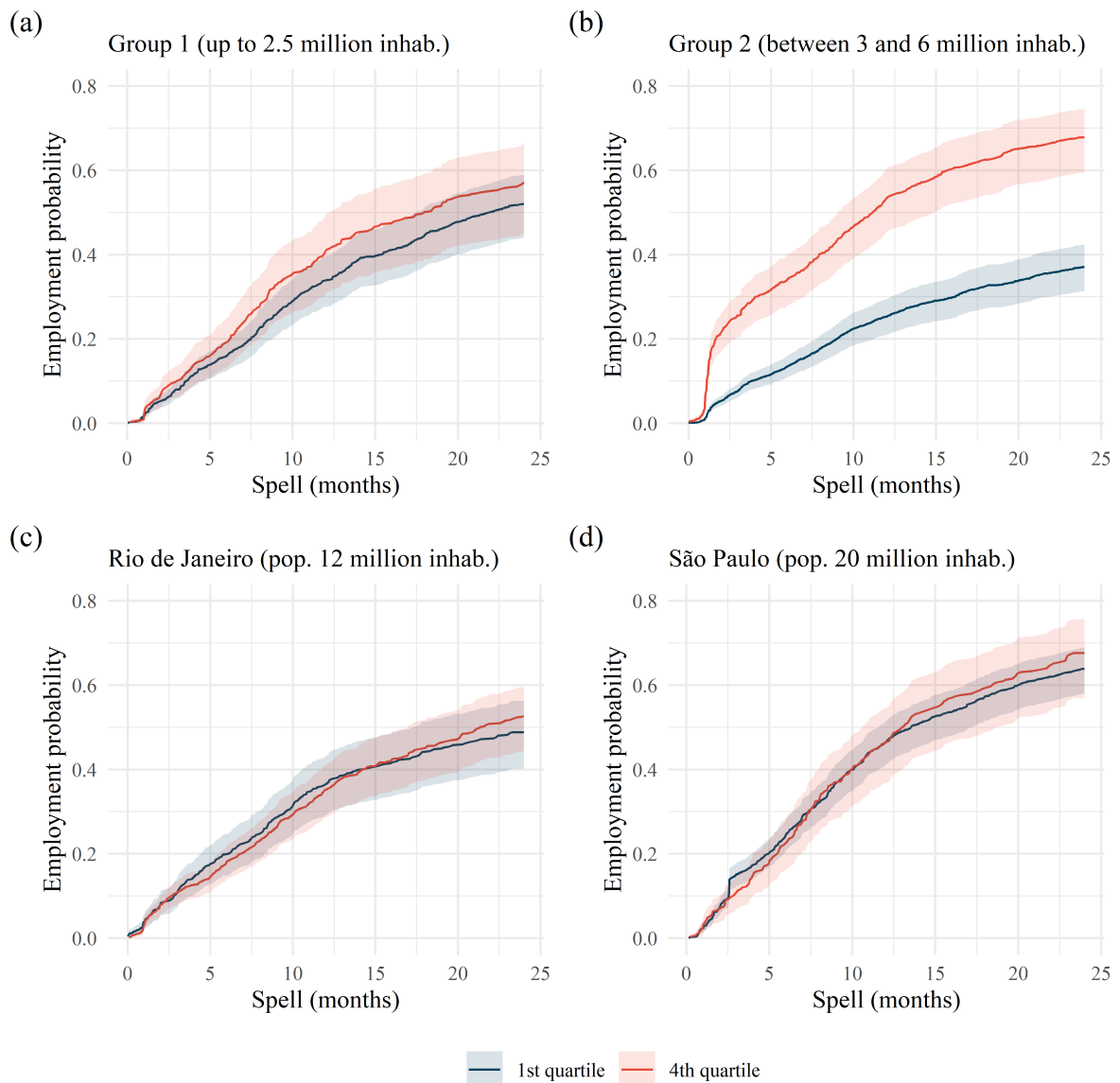
where the spatial availability of job opportunities at origin o , V_o , is the sum of all opportunities available at each destination (P_d) weighted by a balancing factor between each pair (F_{od}^t), which

is an interaction between a population-based effect and an impedance factor to account for the travel cost.

B Results for other accessibility indicators

Figure 5 plots survival analysis using the cumulative accessibility index of opportunities up to 60 minutes of walking distance from the worker's residence, whereas Figure 6 is the equivalent for the competition-based logistic index.

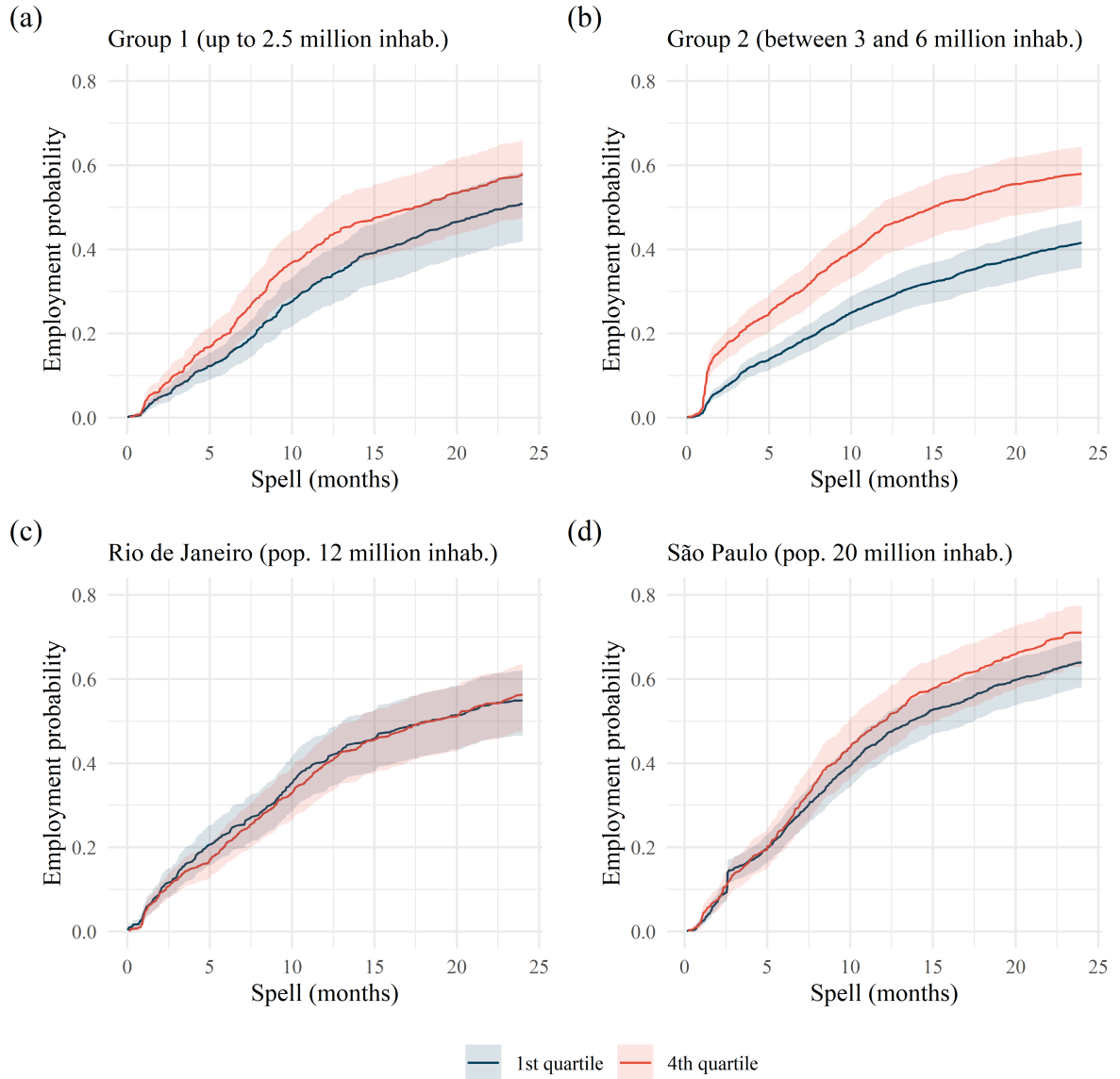
Figure 5: Survival curves for employment probability between city groups, cumulative index



Source: elaborated by the authors.

Notes: Vertical axis corresponds to $1 - survival$; shadowed areas represent 95% confidence interval.

Figure 6: Survival curves for employment probability between city groups, competition index



Source: elaborated by the authors.

Notes: Vertical axis corresponds to $1 - survival$; shadowed areas represent 95% confidence interval.