Research article

Estimating the intra-urban wage premium for a Metropolitan Area in a developing country

Rodger Barros Antunes Campos[1]
rodgercampos@hotmail.com | https://orcid.org/0000-0001-5478-6510

Carlos Roberto Azzoni[1]
cazzoni@usp.br | https://orcid.org/0000-0002-1085-7062

Abstract

We estimated the intra-urban wage premium and its attenuation with a balanced panel of workers in the metropolitan area of Sao Paulo, Brazil. There are few studies dealing with the agglomeration effects on wages in developing countries, especially focusing on a fine geographical scale, as we consider in this paper. We geocoded the employment data on a grid of 9,071 cells of 1 km² and compared wages in the adjoining cells. We use Geographically Weighted Regressions to determine the size of the rings based on the AIC minimization method. We use worker and firm observable characteristics and fixed effects of firm, worker, and cell to deal with the selection of firms and workers. The estimated intra-urban wage premium ranges from 0.8% and 1.1%, depending on the size of the cells (0.5, 1, 2, and 4 km^2). The attenuation effect is observed but restricted to 3 km from the inner cell and is stronger for less educated workers.

Keywords

Agglomeration, Wage attenuation, Intra-urban wage premia, Central business district.

Estimando o prêmio salarial intra-urbano para uma região metropolitana de um país em desenvolvimento

Resumo

Estimamos o prêmio salarial intraurbano e sua atenuação a partir de um painel balanceado de trabalhadores na área metropolitana de São Paulo, Brasil. Existem poucos estudos lidando com os efeitos de aglomeração nos salários em países em desenvolvimento, especialmente focando em uma escala geográfica detalhada, como consideramos neste artigo. Geocodificamos os dados de emprego em uma grade de 9.071 células de 1km² e comparamos os salários nas células

[1]Universidade de São Paulo, SP, Brasil
Recebido: 01/05/2022.
Revisado: 27/08/2023.
Aceito: 20/10/2023.
Publicado: 28/03/2024.
DOI: https://dx.doi.org/10.1590/1980-53575411rcca

adjacentes. Utilizamos Regressões Ponderadas Geograficamente para determinar o tamanho dos anéis com base no método de minimização do AIC. Utilizamos características observáveis de trabalhadores e empresas e efeitos fixos de empresa, trabalhador e célula para lidar com a seleção de empresas e trabalhadores. O prêmio salarial intraurbano estimado varia de 0,8% a 1,1%, dependendo do tamanho das células (0,5, 1, 2 e 4 km²). O efeito de atenuação é observado, mas restrito a 3km da célula interna e é mais forte para trabalhadores menos educados.

Palavras-chave
Aglomeração, Atenuação Salarial, Prêmios salariais intraurbanos, Distrito central de negócios.

Classificação JEL
R23, R15, R12.

1. Introduction

Even though the density-productivity relationship is well established, the geographical scale is a critical aspect that demands more attention since different types of agglomeration externalities operate at different geographical scales (Rosenthal and Strange, 2003a, 2003b). Most studies have focused on comparisons across cities, with less attention to the within-city effect of density on wages. This lack of analysis is more pronounced in developing countries, where suitable databases are lacking (Ahlfeldt and Pietrostefani, 2019). Our study covers the São Paulo Metropolitan Region (SPMR), the largest metropolitan area in Brazil.[1] It is composed of 39 municipalities spread over an area of 7,946 km². Its population in 2017 was 21.6 million, representing 47% of the state's population and 10% of the country's population. The municipality of São Paulo, the state's capital, accounts for 56% of the population in the area.

It is essential to shed light on the net effects of agglomeration both for public policy purposes and for understanding the firms' and employees' location decisions. Public policies that stimulate job sprawling may reduce the gains from agglomeration and increase the costs of providing additional public goods outside the core. The agglomeration and attenuation effects are also important for the private location decisions of firms and employees since location influences productivity and wages. The main question is: How local are the agglomeration effects, and how far

[1] Lack of geocoded data on firms and employees precludes the extension of this study to other metropolitan areas.

do they go? Are there intra-urban agglomeration economies in a developing country, and how do they compare to developed countries? Previous studies on Brazilian cities show that the urban wage premium is not negligible (Rocha, Silveira Neto, and Gomes, 2011; Cruz and Naticchioni, 2012; Silva, Santos, and Freguglia, 2016; Barufi, Haddad, and Nijkamp, 2016; Silva, 2017; 2018). Even controlling for regional cost of living and other variables, wage inequality across metropolitan areas persists (Azzoni and Servo, 2001; Menezes and Azzoni, 2006).

To the best of our knowledge, no attention has been paid to the intra-urban wage premium in cities of developing countries. We work with a massive database of administrative information from the Ministry of Labor, including the characteristics of workers and firms and their addresses. We have assembled a 13-year balanced panel in which each worker and firm is precisely located in the metropolitan space. We identify the intra-urban wage premium and its attenuation in the metropolitan area. Contrary to the typical studies of between-city agglomeration effects, which come up with one sole coefficient for each city, we identify the within-city wage premium and assess how unequal it is in the metropolitan area.

Density was calculated for cells of 0.5 km^2, 1 km^2, 2 km^2, and 4 km^2 to explore the modifiable areal unit problem (MAUP), well known in the empirical literature. To ensure that the job is performed at the firm location, we excluded sectors (e.g., construction) and occupations (e.g., postman) more likely to be performed outside the firm's quarters. Following Combes et al. (2008), we estimate the wage elasticity with respect to employment density. First, we ignore the neighborhood to compare our findings with the empirical literature. As in Rosenthal and Strange (2008), we then control for the neighboring cells to estimate the agglomeration effect and its spatial attenuation. The results indicate a within-city wage premium of 1.1% in our preferred econometric specification, and the premium is larger for workers that are more educated. The agglomeration effect is highly local since it decreases sharply as distance increases, especially for less-educated workers.

The remainder of this paper is organized as follows. In Section 2, we review the related literature. In Section 3, we set out the methodology and our database. Section 4 provides evidence of the within-city wage premium and its attenuation. Section 5 separates the analysis by education level, and Section 6 concludes.

2. Literature review

Focusing on within-city literature (Urban Economics), the Central Business Districts (CBDs) and the Subcenter Business Districts (SBD) are areas within cities with a high concentration of employment compared to other areas. Agglomeration economies and transportation costs are the drivers of business district existence. The demand and supply for goods and services located in the CBD, SBD, or outside of these localities are spatially differentiated. This differentiation explains the heterogeneous wage structure within cities.

Many studies have pointed to the wage differential in large urban centers (Ahlfeldt and Pietrostefani, 2019). There are three sources of the spatial wage heterogeneity[2]: 1) differences in the composition of the labor market, reflecting the skills of the demanded workers; 2) differences in endowments, such as in climate; and 3) interactions amongst workers and firms (Combes et al., 2008). Such elements are present in comparisons of municipalities or metropolitan areas and within-city comparisons. The equilibrium with wage differentials is only stable in the presence of increasing returns derived from agglomeration economies (Jaffe, Trajternberg, and Henderson, 1993; Henderson, 1991; Kim, 1991; Brakman et al., 2009) or in the presence of imperfect competition (Combens, Mayer, and Thisse, 2008).

Sharing, learning, and matching are the mechanisms that activate the economies of agglomeration and increase productivity. The sharing effect involves the gains derived from the division of labor, the reduction in production risks, and the sharing of local infrastructure, a variety of input suppliers, and a pool of workers with similar skills. The matching effect corresponds to the increase in quantity and quality of matches between employees and employers. The learning effect is associated with the knowledge generation, dissemination, and accumulation mechanisms in large and dense markets. (Duranton and Puga, 2004). In the within-urban scale analysis, the firms cluster in different locations to access the net benefits of agglomeration economies. This explains why factories, health, and financial services locate in different areas of a city. Places with employment density and workers' productivity attract more skilled workers and more productive firms (sorting) and accelerate both the stock of human capital and wage growth (Glaeser and Maré, 2001).

[2] Campos and Azzoni (2019) provide an overview of the theoretical and empirical aspects on the subject.

Even though disentangling sharing, learning, and matching is yet to be achieved appropriately, empirical findings on urban wage premia have been provided, ranging between 1% and 11% (Costa and Overman, 2014), with an average of around 4% (Melo, Graham, and Noland, 2009; Combes and Gobbilon, 2014; Ahlfeldt and Pietrostefani, 2019). Most of these analyses deal with the effects of agglomeration at a regional scale (metropolitan region, labor market areas, etc.),[3] which makes it impossible to understand the extent of the agglomeration effects on labor productivity in the intra-urban space (Rosenthal and Strange 2003a, 2003b, Overman, 2004). This is tantamount to assuming that the intra-urban wage premia are homogenous in each place. Results from Rosenthal and Strange (2003a), van Soest et al. (2006), Rosenthal and Strange (2008), and Andersson et al. (2016) reveal that the geographic scope of the externalities of agglomeration is smaller than the size of the city (or metropolitan region).

The debate on wage differentials is also relevant on a less aggregated scale, given that intra-urban spatial heterogeneity implies non-isotropic wages (Fujita, Krugman, and Venables, 1999), reflecting one of the many sources of wage inequality. Labor markets are spatially limited (Glaeser, Resseger, and Tobio, 2009) and follow their own dynamics. From this intrinsic characteristic, the study of intra-urban dynamism helps better understand the effect of agglomeration on wages (productivity) and the spatial distribution of jobs. The New Urban Economics theoretical and empirical literature assumes employment concentration in the intra-urban space as a price anchor,[4] and some studies moved forward by overcoming this condition. Van Soest et al. (2006) measured how agglomeration economies in one location contribute to employment and establishment growth at other locations in one province of the Netherlands. They show that agglomeration economies positively affect the outcome variables, but their effects sharply reduce with distance. Rosenthal and Strange (2008) estimated the relationship of agglomeration and proximity with wages in the United States using concentric circles of 0-5 miles, 5-25 miles, 25-50 miles, and 50-100 miles around the place of the job. They found a positive effect of agglomeration on wages and that the effect is reduced with distance. Andersson et al. (2016) studied wage levels and density in grids of 1 km^2

[3] See Behrens, Duranton, and Robert-Nicoud (2014), Storper and Venables (2004), Baum-Snow and Pavan (2011), Moretti (2011, 2013), Roca and Puga (2017), among others.

[4] These places are labeled central business districts in monocentric cities, or subcenter business districts, in polycentric cities. See Alonso (1964), Muth (1967) and Mills (1967), Brueckner (1987) for a general theoretical model.

cells in selected places in Sweden over 20 years, using the first- and second-order neighborhoods to identify the attenuation effects.

Although this latter study represents a step ahead in analyzing the within-city agglomeration economies, their database did not permit the control for individuals' and firms' non-observed skills and productivity, and their results might be biased. Controlling for individual fixed effects reduces the estimated premium by around 29-22 percentage points (p.p.) compared to cross-section results (Glaeser and Maré, 2001). Yankow (2006) found premia between 8% and 19% without control for non-observed individual skills and between 3.3% and 5% when those are controlled for. Workers' skills are associated with firms' size (Mion and Naticchioni, 2009), and disregarding worker self-selection results in a critical omitted variable problem, which overestimates the results (Combes, Duranton, and Gobillon, 2008). Firms' non-observed characteristics are also important for controlling firms' sorting (Abowd, Kramarz, and Margolis, 1999). Different firms and individuals may benefit differently from the spatial labor market, so the estimation demands a suitable database to identify such sorting.

Having these issues in mind, we move a step ahead. Given the specificities of our database, we perform more robust econometric estimations of the within-city agglomeration economies and the attenuation effects, using a longitudinal database and controlling for the sorting of individuals and firms. We use an empirical approach to select the neighborhood and explore higher orders of the neighborhood as well. The MAUP issue is also explored.

3. Methodology and Database

3.1. The model

The objective is to estimate the wage premium in a dense area, and its attenuation with distance. We use the econometric specification of Combes et al. (2008) and Rosenthal and Strange (2008), but we add controls for firm and individual fixed effects based on Abowd, Kramarz, and Margolis

(1999) and Woodcock (2008; 2015). The complete version of the econometric specification for the wage premium effect is

$$logw_{i,t} = A_{c,t}\rho + S_{c,t}\eta + \beta_c + \mu_k + X_{i,t}\varphi + \delta_i + \psi_j + \epsilon_{i,t} \quad (1)$$

Where $A_{c,t}$ indicates employment density and ρ is a vector of associated coefficients; $S_{c,t}$ indicates localization economies, and η is a vector of the associated coefficients; β_c indicates the area c fixed effects (pure area effect); μ_k denotes industry fixed effects; $X_{i,t}$ is a matrix of time-varying worker characteristics and φ is a vector of the associated coefficients; δ_i and ψ_j are worker and firm fixed effects; and $\epsilon_{i,t}$ is the error term, assumed i.i.d.

To estimate the wage premium attenuation, we assume that $A_{c,t}$ may be linearly (or linearized) decomposed into inner and outer neighbors, as in Rosenthal and Strange (2008). Equation 1 is expanded to

$$logw_{i,t} = \sum_{l=1}^{L} A_{c,t}^{l}\rho_l + S_{c,t}\eta + \beta_c + \mu_k + X_{i,t}\varphi + \delta_i + \psi_j + \epsilon_{i,t} \quad (2)$$

Where $A_{c,t}^{l}$ is job density in cell c at time t, and l represents rings of expansions around cell c (l=1,2,…,L), and ρ_l are the associated coefficients which capture the spatial extension of the effect of agglomeration,[5] and are the parameters of interest. The coefficient ρ_1 shows the agglomeration effect, and ρ_2, $\rho_3 \ldots \rho_l$ capture the attenuation effect. If $\rho_1 > \rho_2 > \rho_3 > 0$ and statistically significant, a wage premium is observed, and it decreases with distance, evidencing attenuation. If $\rho_1 > 0$ and $\rho_2 = \rho_3 = 0$ or $\rho_2 = \rho_3 < 0$, then the agglomeration effect is highly localized in the inner cell alone. If $\rho_3 < \rho_2 < \rho_1 < 0$, there is no evidence of a wage premium.

One critical issue is the selection of rings. Unlike Rosenthal and Strange (2008) and Andersson et al. (2016), in which the rings are arbitrarily defined, we use Geographically Weighted Regressions (GWR) to determine the rings. Our basic equation for employment density is

$$A_c = \beta_0(u_c, v_c) + \varepsilon_c \quad (3)$$

[5] l=1 indicates the cell where the job is localized (inner cell); l=2 denotes cells in the first ring around the inner cell; l=3 indicates the cells in the next ring, and so on.

where A_i is the number of employees in cell c; (u_c, v_c) are the latitude and longitude of the c^{th} *cell centroid*, $\beta_0(u_c, v_c)$ is the kernel-estimated employment average at cell c, and ε_c is the random error term. The GWR estimator for $\beta_0(u_c, v_c)$ is given by

$$\hat{\beta}_0(u_c, v_c) = (X^T W(u_c, v_c) X)^{-1} X^T W(u_c, v_c) \tag{4}$$

where $\hat{\beta}_0$ is the estimated spatial mean, $W(u_c, v_c)$ is a $n\ x\ n$ weight matrix, with null off-diagonal elements and the geographical weights in the main diagonal; X is a $nx1$ vector containing values equal to 1; and the superscript T indicates a transposed vector.

The GWR is a non-parametric estimator for continuous localization functions (u_c, v_c) using kernels and the log-likelihood for each set of estimates and does not provide a single solution. To adjust the optimization, we consider local log-likelihoods and take observations close to the cell c (Bowman and Azzalini, 1997; Fotheringham, Brunsdon, and Charlton, 2002). Thus, estimating GWR involves the selection of bands (or windows) for an isotropic kernel spatial weight function, such as the Gaussian, Tricubic, and Bisquare functions, for example. The size of the windows is based on the Akaike Information Criterion (AIC) minimization method (Fotheringham et al., 2000). Since the AIC provides the optimal distance between the cell where the worker i is located and the set of cells in the neighborhood, we can identify the number of rings l of Equation 2.

Even controlling for worker and firm observable characteristics, and a set of fixed effects there might be unobserved worker's ability or firms' sorting embodied in the error term $\epsilon_{i,t}$ (Equation 5). Geology variables (Combes et al., 2008) and Bartik instrumental variables (Silva, 2017) have been used as instruments to control for endogeneity. These are not suitable in this case, for the instrumental variable must be time-variant and as granular as the cells of the grid, and very few variables have such characteristics.[6] To compare our findings with those in the empirical literature, we present the results as elasticities in the case of the wage agglomeration premium. For the wage premium attenuation, we use the semi-elasticity functional form to give less weight to closer employment than to employment located at outer rings, as in Rosenthal and Strage (2008).

[6] Bartik instrumental variables could be a solution, but there is no information available at such a detailed geographical level.

3.2. Database

The data set comprises a balanced panel of workers covering 2002-2014. Each firm legally established must provide the Ministry of Labor with annual information regarding their employees.[7] The database consolidates 99% of the universe of the formal labor market and is considered a census of formal workers. Identification markers permit the creation of a matched employer-employee database. The microdata allows following the trajectory of workers geographically (municipality, state), sectorally, occupationally, and personally (age, tenure, gender, etc.). Selected information on the firms is also available (size, location, sector of activity). Based on the firm's addresses, it was possible to associate geographical coordinates with each firm and their workers.[8]

Our database contains 18-65-year-old individuals working more than 20 hours per week in a private firm. We have selected the one with the highest wage for workers with more than one labor contract. The panel data comprises 4,573,205 observations, corresponding to an annual balanced panel with 381,785 employees, 112,340 firms, and 318,076 firm--worker matches. We use the hourly wage in December each year as the dependent variable. As for the covariates, we use four cycles of education; age, age squared; tenure, tenure squared; gender; firm size; sector; and sectorial specialization[9] (mix of activities in each cell). Employment density (number of jobs per km^2) is the critical variable. Since we use same-size cells of 1 km^2 as the geographical unities, there are no problems related to distinct area sizes and gross and net employment density problems (Ciccone and Hall, 1996; McDonald, 1987; McMillen, 2001). Figure 1 shows the grid of cells.

[7] RAIS – Relação Annual de Informações Sociais is a report compulsorily requested to formal establishments (public and private). Firms must complete the report annually, and the Ministry of Labor is responsible for managing the information. It covers only formally established (incorporated) organizations (public and private) and workers with a labor card. It leaves out informal organizations and non-wage labor relations (self-employed, temporary work, etc.). Firms in the public sector were excluded, given that wage formation is peculiar in those activities.

[8] Geocodification was based on the street shapefile produced by the Centro de Estudos da Metropole (CEM, 2016) and the World Locator (online street shapefile) in ArcGIS. The geocoding procedure is available upon request to the authors.

[9] It is the total number of workers in sectors over the total number of workers in the Metropolitan Area of São Paulo (MASP). This index control for the level of sectoral specialization in the economy of the MASP.

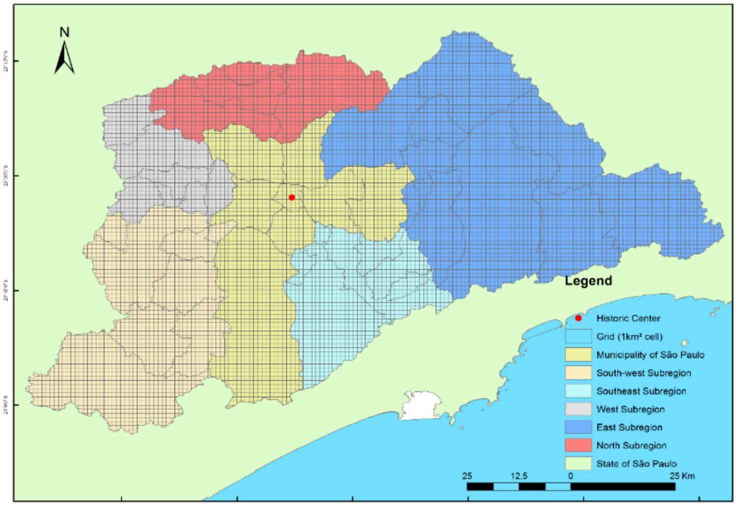

Figure 1 - Grid of 1 km^2 cells

Source: authors elaboration using IBGE shapefiles

We have plotted all firms on the grid and summed up the number of employees by cell. The cell where the employee is located is called the inner ring (l = *1*), and the surrounding cells are considered as first-order (l = *2*) and second-order neighbors (l = *3*) (or first- and second-order rings), as displayed in Figure 2. To identify the attenuation effects, we consider the average number of employees in the cells of the corresponding rings.

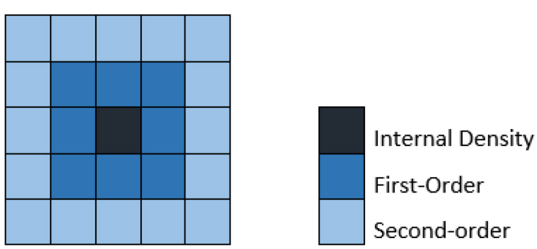

Figure 2 - Cells and Neighbors

Source: authors elaboration

4. The effect of density on wages

Table 1 presents the descriptive statistics of the non-categorical variables. Hourly wages were deflated correctly.[10] The average hourly wage is R$ 14,69, approximately USD 3.90 as of the November/2018 exchange rate. There is enough employment density variance across cells for the identification of the agglomeration effect. Figure 3 shows the spatial distribution of jobs in 2002 and 2014. The clusters with the highest densities are in São Paulo City (the state's capital), Barueri City, and the ABCD region. As shown in Table 1, the density variance is large, and the average in the inner cells is 10,671, decreasing to 68% and 57% of this average in the cells in the first and second-order rings. Table A1 in the Appendix shows that 10% of firms move across cells, 11% of employees move across firms, and 13% move across cells. Thus, there is enough information for the fixed effects identification.

Table 1 – Descriptive statistics of the non-categorical variables

Variable	Mean	Std. Dev.	Min.	Max.
Ln (Wage)	1.97	1.19	-2.85	6.74
Wage	14.69	24.26	0.058	845
Inner cell density (Density)	10,671	14,104	1	115,546
First-order density (WDensity)	7,235	7,815	0	44,642
Second-order density (W2Density)	6,112	5,954	0	26,821
Tenure (month)	111.24	83.26	0	598.9
$Tenure^2$	19,307	26,516	0	358,681
Age (year)	39.10	9.05	18	65
Age^2	1,610	731	324	4,225
Specialization Index*	1	1.13	0.0001	14

Source: author's elaboration based on RAIS data. *Share of workers in sector s in the cell

[10] We have used the IPC-Fipe consumer price index calculated for the city of São Paulo.

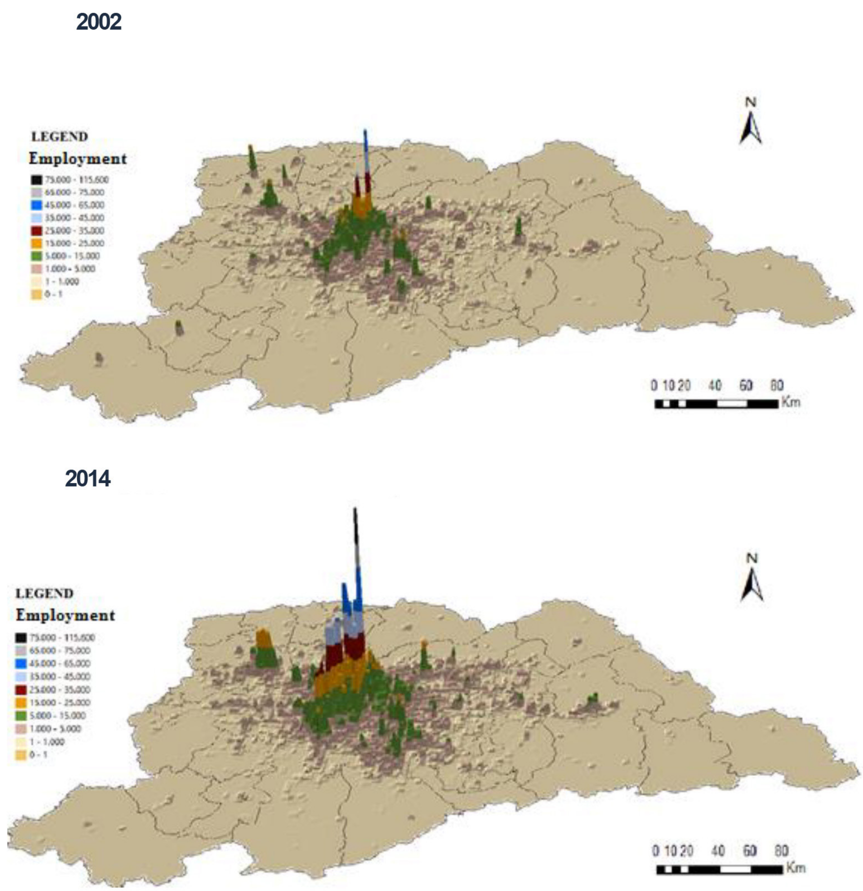

Figure 3 - Spatial distribution of jobs

Source: authors´ elaboration from RAIS data

Table 2 reports the results of our basic regression (Equation 1) with POLS and Fixed Effects estimators. As we estimate log-log models, the coefficients are elasticities. If no controls are included, as in the first column, the wage level in a cell increases by 17.6% when density doubles. As covariates are included in the subsequent columns, the wage premium is progressively reduced. It even becomes negative in column POLS V. As we mentioned before, it is necessary to deal with the sorting of firms and workers due to their unobserved characteristics. In controlling for workers' fixed effects, we deal with highly skilled workers who self-select to work in dense areas, for example. The identification of workers' fixed effects comes from workers' movement between jobs and firms moving across cells. It is recognized that the movers may not represent all workers and firms and that the movements are not randomly decided. Given data limitations, using fixed effects is the only way to reduce the bias.

In columns FE I to FE IV, we progressively add covariates and fixed effects, and the density effect is always positive and statistically significant at 1%. Just by adding the worker fixed effect, the density coefficient drops to 0.6%. As it is well-known, productive firms are also attracted to dense cells, and such self-selection demands controlling for sorting. In column FE II we replace workers for firms fixed effects, and the elasticity is similar to the previous column (0.62%). Following Abowd, Kramarz, and Margolis (1999) and Woodcock (2008; 2015), we include both fixed effects simultaneously and find that doubling density leads to a wage increase of 0.33%, about half of the effect in the previous two columns.

Public infrastructure tends to be provided in specific places for biases in public policy, historical path dependence, etc. To consider that, we keep the worker and firm fixed effects and add cell fixed effects. We encounter a wage premium of 1.02% (last column), larger than in the previous three columns. The increase in the density effect resulting from the inclusion of unobservable characteristics of the cells is related to local characteristics that contribute to receiving firms and workers, such as aptitude to attract determined types of business, etc. This effect is only relevant when associated with the sorting of firms and workers, as a comparison of columns POLS V and FE IV indicates. Ahlfeldt and Piestrostefani's (2019) meta-analysis of 28 studies indicates an average wage-density elasticity is 5% percent, with a standard deviation of 4%, and an average productivity--density of 8%, with a standard deviation of 4%. Larson (2013) finds results between 0.72% and 0.83% without controlling for fixed effects. Our results indicate a smaller intra-urban wage premium than those estimated across municipalities or districts.

Table 2 – Estimated Intra-Urban Wage Premia

Variables	POLS I	POLS II	POLS III	POLS IV	POLS V	FE I	FE II	FE III	FE IV
Density	0.1766***	0.1135***	0.0548***	0.04938***	-0.0105***	0.0060***	0,0062***	0.0033***	0.0102***
Controls	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	No	No	No	No	Yes	No	No	No	Yes
Individual FE	No	No	No	No	No	Yes	No	Yes	Yes
Firm FE	No	No	No	No	No	No	Yes	Yes	Yes
R^2	0.0344	0.5301	0.7701	0.7714	0.7912	0.9566	0.8712	0.9641	0.9643
Obs.	4,573,205	4,573,205	4,573,205	4,573,205	4,573,205	4,573,205	4,573,205	4,573,205	4,573,205

Source: authors' elaboration from RAIS data. Note: Cells of 1 km^2. Controls included: tenure, $tenure^2$, education, firm specialization, and municipality dummies. The POLS specification includes gender, age, age2, and sector of activity additionally. Significance: 1% (***), 5% (**), and 10% (*). Standard error adjusted for individual clusters.

How sensible are the last results when the cell size changes? The empirical literature does not stress this question due to data limitations, but we can check the sensitivity of our results to different cell sizes. We estimate the same models using cell sizes of 0.5 km^2, 2 km^2, and 4 km^2. The density adjusted to 1 km^2 decreases as the cell area increases, as the last column in Table 3 reveals. In the POLS specification without controls, the coefficient decreases as the cell size increases, but that is not the case in the other specifications. Controlling for all observable and non-observable variables (FE IV), the estimated wage premium elasticity for 0.5 km^2 cells is 1.12%, just above the 1.02% found for 1 km^2 cells presented before. For 2 km^2 cells, the elasticity is half the value for 0.5 km^2 cells, and the value increases for 4 km^2 cells. This pattern aligns with Larsson (2013), confirming that smaller areas provide higher wage premia. Denser areas facilitate the sharing of knowledge and other interaction effects, compared to less dense areas. These findings also indicate that the relationship between the geographic scale and the wage premium is not linear.

Table 3 – Sensitivity to cell size

Cell size		POLS I (no controls)	POLS V [(a)]	FE IV [(a)]	Employment density (Adjusted Mean to 1 km^2)[(c)]
0.5 km^2	Coeff.	0,3801***	0,0241***	0,0112***	12,814
	R^2	0.04	0.79	0.96	
1 km^2 [(b)]	Coeff.	0.1766***	-0.0105***	0.0102***	10,671
	R^2	0.03	0.79	0.96	
2 km^2	Coeff.	0,0729***	-0,0017***	0,0056***	9,164
	R^2	0.02	0,79	0.96	
4 km^2	Coeff.	0,0393***	0,0021***	0,0085***	8,291
	R^2	0.03	0.79	0.96	

[(a)] All controls and fixed effects included, as in Table 2; [(b)] From Table 2. [(c)] Table A2 presents the descriptive statistics of employment density by different cell sizes. Note: Table A3 presents the results for the other econometrics specification, considering different cell sizes.

5. Attenuation effects

Urban Economics models usually use the Business Central District (CBD) as a reference point in estimating wage gradients. Since we do not have any specific anchor, we compare the wage levels in the inner cells with those in the surrounding cells. Although this approach is more flexible, it faces the challenge of determining the optimal number of neighboring cells. If a particular cell *c* is highly dense, the wage levels tend to decrease as we move away from it. However, as the distance increases, we might approach another dense cell, and the wage level increases by the influence of this latter cell. Therefore, as the spatial distribution of employment is not isotropic, we need an empirical approach to select the optimal distance from the inner cell.

We use GWR to estimate local means of employment concentration by using subsamples.[11] To select the subsamples, we find the kernels' optimal bandwidth that minimizes the information criteria. We consider different kernel functions (Gaussian, Bisquare, and Tricubic) and select the associa-

[11] This approach is also used to identify subcenter business districts (McMillen and Mcdonalds, 1997; McMillen, 2001; Redfearn, 2007).

ted distance based on the AIC. The Tricubic kernel function minimizes the AIC criteria for all years. It indicates an average bandwidth of 2,07 km, determining two rings around the inner cell as the optimum number (Table A4, in the Appendix). To avoid giving too much weight to the inner cell compared to cells located in the outer rings, we use a log-linear functional form, as proposed by Rosenthal and Strange (2008). From now on, all results are expressed in semi-elasticities, and the coefficients are normalized to 100,000 workers. They inform the direct and indirect effects (spillovers) on the wage levels (in logs) of the inner cell of adding 100,000 new workers in that cell or surrounding cells.

Table 4 reports the results of the attenuation models using the full econometric specification. All estimations provide positive agglomeration effects in the inner rings. Adding 100,000 workers in a ring is associated with wages between 2.5% and 6% higher (Columns FE I – FE X). Despite the change in functional form, the positive and significant coefficient in the inner cell confirms the result previously shown in Tables 2 and 3. It is in line with the empirical studies that use the semi-elasticity functional form. In column FE II we add the first ring of cells around the inner cell. The resulting wage premium of the inner cell almost doubles, and the premium for the cells of the first ring is negative, showing evidence of attenuation. The increase in the wage premium in the inner cell when the outer ring is included suggests that agglomeration effects spillover from the surrounding cells into the inner cell. Column FE III adds the second ring of cells, with similar coefficients for the inner cell and the first ring, and the coefficients for the cells in the second ring are negative but insignificant. Adding the third ring of cells gives similar results for the first two layers, but the coefficient becomes positive, although not significant.

Table 4 – Estimated Intra-Urban Wage Premia Attenuation

	FE I	FE II	FE III	FE IV	FE V	FE VI	FE VII	FE VIII	FE IX	FE X
Density	0.0248***	0.0547***	0.0554***	0.0552***	0.0550***	0.0587***	0.0573***	0.0604***	0.0576***	0.0601***
WDensity	-	-0.1180***	-0.1089***	-0.1095***	-0.1833***	-0.2049***	-0.1849***	-0.1796***	-0.1486***	-0.1427***
W2Density	-	-	-0.0183	-0.0229	-0.1657***	-0.1709***	-0.2077***	-0.1984***	-0.1479***	-0.1276***
W3Density	-	-	-	0.0086	-0.3788***	-0.5241***	-0.5488***	-0.5496***	-0.5524***	-0.5283***
W4Density	-	-	-	-	0.9795***	0.6816***	0.6290***	0.5940***	0.5443***	0.5451***
W5Density	-	-	-	-	-	0.7625***	0.3578***	0.3020***	0.2121***	0.2112***
W6Density	-	-	-	-	-	-	0.8117***	0.6434***	0.4901***	0.4272***
W7Density	-	-	-	-	-	-	-	0.3993***	-0.0847	-0.2352**
W8Density	-	-	-	-	-	-	-	-	1.1298***	0.8158***
W9Density	-	-	-	-	-	-	-	-	-	0.7223***
R^2	0.9643	0.9643	0.9643	0.9643	0.9643	0.9643	0.9643	0.9643	0.9643	0.9643
Obs.	4,573,205	4,573,205	4,573,205	4,573,205	4,573,205	4,573,205	4,573,205	4,573,205	4,573,205	4,573,205

Source: authors' elaboration from RAIS data. Note: Cells of 1 km^2. The specifications include tenure, tenure^2, education, firm specialization, and fixed effects of time, municipality, cell, individual and firm. Standard error adjusted for individual clusters.

If we restrict the distance to 2 km, the attenuation in the wage premium is clear. It is in line with the canonical models of Urban Economics and the results of Andersson et al. (2016). In the remaining columns of Table 4, we add more rings around the inner cell and observe the effects on the results. The coefficients for the wage premium in the inner cell are similar in the additional columns, and so is their attenuation in the first two rings. However, as more cells are added, the coefficients change signs, and no attenuation pattern is formed. As mentioned above, as the distance from the inner cell increases, the chances of getting close to another dense cell also increases, which helps to explain the observed results. This price gradient format is well-discussed in theoretical models that deal with multiple centers (Lucas and Rossi-Hasnberg, 2002; Wred, 2015; Ahlfeldt et al., 2016). On the other hand, the bandwidth selection based on GWR proved to be adequate, providing a proper isotropic area to measure the attenuation effect.

As the maps showing the distribution of jobs in the metropolitan area indicate, three subcenter business districts exist in the area.[12] We now perform an exercise just with the cells in those areas and estimate the attenuation effect, which might involve cells located outside that area. As the results in the upper part of Table 5 show, the wage premium in the inner cell is similar to the ones shown before (between 0.055 and 0.07), and the attenuation is present beyond the second ring of cells up to the seventh ring (column FE VIII). Thus, if we consider only the denser cells, we replicate the attenuation pattern of studies that measure it from a single CBD.

To complete the exercise, we replicate the estimation just for cells outside the denser areas, again including all cells to measure attenuation. As it can be seen in column FE I of Table 5, the wage premium for the inner cell is more than five times larger than in the previous case, indicating that relatively high density in an area composed of low-density cells provides more advantages, comparatively, than in a dense area. However, once the first ring is added (column FE II), the coefficient loses significance, and no attenuation pattern is observed. Therefore, there is no evidence of a wage premium outside the SDBs. In a study comparing over 360 labor market areas in Brazil, Silva (2017) estimates a wage premium of 3.3% for the São Paulo metropolitan area, employing a similar set of models and variables as in our study. Our results indicate that this premium comes from a specific part of the area, the SDB. This comparison illustrates the usefulness of estimating the intra-urban wage premium since a better understanding of where it is formed within cities can be obtained.

[12] Campos and Azzoni (2021) have determined the existence and extension of such centers in the metropolitan area.

Table 5 –Wage premia attenuation in different parts of the area

	FE I	FE II	FE III	FE IV	FE V	FE VI	FE VII	FE VIII	FE IX	FE X
Cells in the SDB (1,530,924 observations)										
Density	0.062***	0.066***	0.066***	0.068***	0.068***	0.067***	0.067***	0.065***	0.066***	0.065***
WDensity	-	-0.055**	0.010	0.001	0.004	0.013	0.013	0.011	-0.020	-0.024
W2Density	-	-	-0.346***	-0.287***	-0.285***	-0.291***	-0.290***	-0.292***	-0.347***	-0.375***
W3Density	-	-	-	-0.321***	-0.315***	-0.274***	-0.274***	-0.270***	-0.243***	-0.263***
W4Density	-	-	-	-	-0.048	0.025	0.024	0.030	0.142*	0.148**
W5Density	-	-	-	-	-	-0.397***	-0.392***	-0.379***	-0.349***	-0.327***
W6Density	-	-	-	-	-	-	-0.021	0.012	0.167	0.231*
W7Density	-	-	-	-	-	-	-	-0.200	-0.098	0.176
W8Density	-	-	-	-	-	-	-	-	-1.419***	-1.160***
W9Density	-	-	-	-	-	-	-	-	-	-1.178***
R^2	0.9685	0.9685	0.9685	0.9685	0.9685	0.9685	0.9685	0.9685	0.9685	0.9685
Cells outside the SDB (556,667 observations)										
Density	0,3213*	0,2917	0,3055	0,2843	0,2908	0,3095	0,3098	0,3127*	0,3158*	0,3172*
WDensity		2,1004***	2,3265***	2,0981***	2,2540***	2,1553***	2,2680***	2,2699***	2,2751***	2,2945***
W2Density			-0,7210	-1,6839***	-1,3552**	-1,5202***	-1,4306**	-1,4544**	-1,4109**	-1,3793**
W3Density				2,1583***	2,9195***	2,6001***	2,7445***	2,7106***	2,6547***	2,6593***
W4Density					-1,4806***	-2,1271***	-1,7053***	-1,7317***	-1,7867***	-1,8341***
W5Density						1,3468**	2,3473***	2,2606***	2,1728***	2,0921***
W6Density							-1,8332***	-2,0163***	-2,2679***	-2,3503***
W7Density								0,3311	-0,0031	-0,1918
W8Density									0,6888	0,4591
W9Density										0,5439
R^2	0.9691	0.9691	0.9691	0.9692	0.9692	0.9692	0.9692	0.9692	0.9692	0.9692

Source: author's elaboration based on RAIS data. Note: Cells of 1 km^2. Controls: tenure, $tenure^2$, education, firm specialization, municipality dummies, and fixed effects for time, municipality, cell, individual and firm. Significance: 1% (***), 5% (**), and 10% (*). Standard error adjusted for individual clusters.

6. Human Capital: Agglomeration and Attenuation Effects

Cities are centers of innovation, production, and marketing of ideas (Jeffe, Trajtenberg, and Henderson, 1993). However, the appropriation of such ideas depends on the absorption ability of individuals, which is related to their educational level (Cohen and Levinthal, 1990). Studies for Brazil show the same pattern (Falcão and Silveira Neto, 2007; Silva, 2018). High-skilled workers have more ability to communicate and, consequently, to learn and to appropriate knowledge that is tacitly in the air, resulting in increased labor productivity compared to low-skilled ones (Storper and Venables, 2004). In other words, workers with limited educational attainment would have less potential to benefit from agglomeration than highly skilled workers. In this sense, the benefits generated by agglomeration, which stimulates the flow of knowledge and information, are relevant for workers and firms to whom such a flow matters the most (Glaeser, 1999; Moretti, 2004a and 2004b; Bathelt, Malmberg and Maskell, 2004; Storper and Venables, 2004; Rosenthal and Strange, 2008; Boulolod, Blum and Strange, 2010; Andersson et al., 2016).

The discussion of human capital in this subsection is limited to workers' heterogeneity in educational attainment. Although there are other elements to human capital (Bacolod, Blum, and Strange, 2009), education is a relevant component (Winter, 2013). We run separately two regressions for workers with less than college and with college or more. As before, we use a log-log functional form when no controls for outer rings are included and a log-linear form when they are. Table 6 reports the results. As expected, workers with a college degree or more attain wage premia 1.7 times larger than workers with less than college, although these also benefit from agglomeration with less intensity. If density doubles, a worker without college gets a 0.8% wage increase, 22% lower than the average shown in Table 2. For a college-educated worker, the wage increase is 1.16%, about 8% larger than in Table 2. Compared to the estimates of Andersson et al. (2016) for Sweden and Rosenthal and Strange (2008) for the US, these effects are smaller. The difference might come from the fact that we control for individual and firm sorting simultaneously, which tends to reduce the effect of density.

As the surrounding cells are included in the computations, columns FE II and FE IV, it is observed that wages increase with inner cell density for both groups, with larger effects for workers with college or more.

Attenuation is observed for less educated workers, although the negative effect in the second ring is lower than in the first ring. These workers face sharp decay in wages as the distance increases. No attenuation is observed for educated workers, indicating that their wage premium has a broader geographic scope. In contrast, low-skilled workers are spatially restricted to the internal ring.

Table 6 –Wage Premium by Educational Level

	Less than College		College and +	
	FE I	FE II	FE III	FE IV
Density	0.0083***	0.0296***	0.0116***	0.0508***
WDensity	-	-0.2180***	-	0.0480
W2Density	-	-0.1168***	-	0.2034***
R^2	0.9660	0.9605	0.9544	0,9545
Obs.	3,503,220	3,503,220	1,069,985	1,069,985

Source: author's elaboration based on RAIS data. Note: Cells of 1 km^2. Controls: tenure, tenure^2, education, firm specialization, municipality dummies, and fixed effects for time, municipality, cell, individual and firm. Significance: 1% (***), 5% (**), and 10% (*). Standard error adjusted for individual clusters. We use log-log functional forms for FE I and FE III and log-linear functional forms for FE II and FE IV.

7. Final Remarks

We have estimated the intra-urban wage premium and its attenuation with distance in the metropolitan area of Sao Paulo, Brazil. We use a balanced panel of workers for 2002–2014, dispersed in a fine grid of 1km *x* 1km cells. The application to a large city of a developing country and the detailed geographical scale are important novelties of the study. We do not impose the central business centers (CBD) or sub-centers (SBD) exogenously, but we estimate the wage premium for each cell and layers of surrounding cells. Based on the wage premium estimated in these three layers, we estimate the attenuation effect resulting from increasing employment density in the inner cell. This way of estimating the wage premium and its attenuation in space is novel to the literature.

The main findings indicate an intra-urban wage premium of 1.02% in the grid with 1 *x* 1 km cells. We estimate the same models for smaller and larger cells, and find wage premia of 1.12% for 0.5 x 0.5 km cells, 0.56%

for 2 x 2 km cells, and 0.85% for cells of 4 x 4 km. Although the premium decreases as we move from 0.5 x 0.5 km cells to 2 x 2 km cells, it increases when moving from the latter to 4 x 4 km cells, indicating non-linearity between cell size and wage premium.

Once the wage premium is estimated, we explore its attenuation with distance from the inner cell. We find evidence that attenuation occurs in neighboring cells up to 2 km apart from the inner cell. We experiment with larger distances and find that beyond 2 km, the wage premium might increase or decrease without an established pattern. This is related to the possibility of getting closer to another dense cell as distance increases since the grid is highly detailed. An exercise selecting only cells of the denser areas but including all areas to evaluate attenuation replicates the typical result obtained in studies considering the existence of one CDB. On the other hand, for cells located outside the denser areas, the wage premium for the inner cell is times larger than for cells in the SDB, but no attenuation pattern is observed. Therefore, there is no evidence of a wage premium outside the SDBs. This opposing of results for inner areas and cells outside the larger agglomerations brings interesting information for policy design. The inner areas are responsible for most of the wage premium observed in the metropolitan area and seem to perform autonomously in attracting business but rewarding less to the city's productivity. On the other hand, denser areas outside the SDBs present higher impacts on productivity, but their effects are restricted in space, limiting their attractiveness to receiving additional establishments. Therefore, instruments contributing to spreading the effects of third-level SDBs might generate better returns to the city's productivity. In this sense, these results indicate that the administrations should promote the attractiveness of areas outside the SDBs.

The heterogeneity analysis revealed that workers with college-level education benefit the most from the increased interaction possibilities given by employment density and can capture positive effects from their neighbors. Although still benefiting from agglomeration, workers with less than a college education obtain just 58% of the educated worker's premium. Attenuation in the 2 km range is evident for the latter type of worker but not for educated workers, for whom the range is not limited to the first ring around the inner cell.

This paper also sheds light on multiple business center issues. Unlike the traditional models that consider a monocentric city, we discuss the role of multiple business centers for the attenuation effect and how local the productivity spillovers are. The high density in the business centers affects workers' productivity (here measured by hourly wage) when the distance from inner cells increases. These results indicate that the Sao Paulo Metropolitan Area is a multiple-center city. When we consider short distances, our attenuation effects findings align with the results of Andersson et al. (2016) and Rosenthal and Strange (2008). However, for neighborhoods localized at more than 2 km distance far from the inner cell, we encounter different results.

For lack of detailed information, we concentrated the analysis on incorporated firms and workers with a labor card. Thus, we restrict the analysis to the formal part of the metropolitan economy. Considering the workers with formal and informal jobs, and those working in the public sector, the share of formal jobs in the state of Sao Paulo in 2021-2022 was 84%.[13] If we add the self-employed ("conta própria") and entrepreneurs to the number of employed people, the formal jobs share drops to 49.8%. These two categories are a hybrid between employment and entrepreneurship, most probably closer to the latter. Since our study deals with between 50% and 84% of all workers, it is important to discuss how this limitation might affect our conclusions. Working with the formal part of the economy would only bring problems to our results if the wage premium and its attenuation deferred for formal and informal workers. Unfortunately, we could not find information to verify that. However, as the wages reflect the productivity of the firms, it is reasonable to argue that the same agglomeration advantages would accrue both to formal and informal activities. Considering the high share of formal employees (84% if we restrict the comparison to workers only), even if they presented strong differences, the final result would be close to the ones we presented since their quantitative importance would be minor. Nevertheless, this is a topic for further investigation once a new population census is available.

[13] IBGE, PNAD Contínua, https://sidra.ibge.gov.br/pesquisa/pnadca/tabelas

References

Abowd, J. M.; Kramarz, F.; Margolis, D. N. 1999, "High-wage workers and high-wage firms." *Econometrica* 67 (2): 251-333.

Alonso, W. *Location and Land Use.* Cambridge: Harvard University Press, 1964.

Andersson, M.; Klaesson, J.; Larsson, J.P. 2016. "How local are spatial density externalities? Neighborhood effects in agglomeration economies?" *Regional Studies* 50 (6): 1082-1095.

Ahlfeldt, G. M. et al. 2016. "The economics of density: evidence from the Berlin wall." *Econometrica* 83 (6): 2127-2189.

Ahlfeldt, G. M.; Pietrostefani, E. 2019. "The economic effects of density: a synthesis." *Journal of Urbana Economics* 11: 93-107.

Azzoni, C.; Servo, L. 2001. "Education, cost of living and regional wage inequality in Brazil." *Papers in Regional Science* 81(2): 157-175.

Bacolod, M.; Blum, B. S.; Strange, W. C. 2009. "Skill in the city." *Journal of Urban Economics* 62 (2): 136-153.

Barufi, A. M. B.; Haddad, E. A.; Nijkamp, P. 2016. "Industrial scope of agglomeration economies in Brazil." *Annals of Regional Science* 56: 707-755.

Bathelt, H.; Malmberg, A.; Maskell, P. 2004. "Clusters and knowledge: local buzz, global pipelines and the process of knowledge creation." *Progress in Human Geography* 28: 31-56.

Baum-Snow, N.; Pavan, R. 2011. "Understanding the city size wage gap." *The Review of Economic Studies* 79(1): 88–127.

Behrens, K.; Duranton, G.; Robert-Nicoud, F. 2014. "Productive cities: Sorting, selection, and agglomeration." *Journal of Political Economy* 122(3): 507–553.

Bowman, A. W.; Azzalini, A. *Applied smoothing techniques for data analysis: the kernel approach with S-plus illustrations.* Oxford: Oxford Science Publications, 1997.

Brakman, S.; Garretsen, H.; Van Marrewijk, C. *The New Introduction to Geographical Economics.* Cambridge, UK: Cambridge University Press, 2009.

Campos, R. A. C.; Azzoni, C. R. 2019. "Dispersão concentrada do emprego intra-urbano: modelos teóricos e abordagens empíricas.» *Revista Brasileira de Economia Regional e Urbana* 13: 606-627.

Campos, R. B. A.; Azzoni, C.R. 2021 "Empirical identification of intra-urban subcentralities: a new methodological approach with an application for a developing country." *Journal Economía* 44: 56-73.

Ciccone, A.; Hall, R. E. 1996. "Productivity and the density of economic activity." *American Economic Review* 86: 54-74.

Cohen, W. M.; Levinthal, D. A. 1990. "Absorptive capacity: a new perspective on learning and innovation." *Administrative Science Quarterly* 35: 128-152.

Combes, P. P.; Duranton, G.; Gobillon, L. 2008. "Spatial wage disparities: Sorting matters!" *Journal of Urban Economics* 63(2): 723–742.

Combes, P. P.; Gobillon, L. 2014. "The empirics of agglomeration economies." Institute for the Study of Labor. Discussion Paper No 8550.

Combes, P.P., Mayer, T., Thisse, J.F. *Economic Geography.* Princeton: Princeton University Press, 1st Edition, 2008.

Costa, S.; Overman, H. G. 2014. "The urban wage growth premium: sorting or learning?" *Regional Science and Urbana Economics* 48: 168-179.

Cruz, B. O.; Naticchioni, P. 2012. "Falling urban wage premium and inequality trends: evidence for Brazil." *Investigaciones Regionales* 24: 91-113.

Duranton, G.; Puga, D. “Micro-foundations of urban agglomeration economies.” In: Henderson, J. V., Thisse, J.F. (Eds.) *Handbook of Regional and Urban Economics,* 4. Amsterdam: North –Holland, 2004.

Falcão, N.Silveira Neto, R. “Concentração espacial de capital humano e externalidades: o caso das cidades brasileiras.” In: *Encontro Nacional de Economia – ANPEC,* 35. 2007, Recife, Pernambuco. Anais... Recife: Anpec, 2007.

Fotheringham, A. A.; Brunsdon, C.; Charlton, M. *Geographically Weighted Regression: the analysis of spatially varying relationships.* Wiley, New York, NY, USA, 2002.

Fotheringham, A. A.; Brunsdon, C.; Charlton, M. *Quantitative geography: a perspective on spatial data analysis.* Sage, London, England, 2000.

Freguglia, R. S. Procópio, T. S. 2013. “Efeito da mudança de emprego e da migração interestadual sobre os salários no Brasil formal: evidências a partir de dados em painel.” *Pesquisa e Planejamento Econômico* 43(2): 255-278.

Fujita, M.; Krugman, P.; Venables, A. *The Spatial Economy: Cities, Regions, and International Trade.* Cambridge: Massachusetts Institute of Technology (MIT Press), 1999.

Glaeser, E.; Resseger, M.; Tobio, K. 2009. “Inequality in cities.” *Journal of Regional Science* 49 (4): 617-646.

Glaeser, E. 1999. “Cities, information and economic growth.” *Cityscape* 1: 9-47.

Glaeser, E; Maré, D. 2001. “Cities and skills.” *Journal of Labor Economics* 19 (2): 316-342.

Haddad, E. A.; Barufi, A. M. B. 2017. “From rivers to roads: spatial mismatch and inequality of opportunity in the urban labor market of a megacity.” *Habitat International* 68: 3-14.

Henderson, J. V. 1991. “Industrial development in cities.” *Journal of Political Economy* 102: 1067-1091.

Henderson, J. V. 2003. “Marshall’s scale economies.” *Journal of Urban Economics* 53: 1-28.

Jeffe, V.; Trajtenberg, M.; Henderson, R. 1993. “Geographic localization of knowledge spillovers.” *Quarterly Journal of Economics* 108: 577-599.

Kim, S. 1991. “Labor specialization and the extent of the market.” *Journal of Political Economy* 97: 692-705.

Larsson, J. P. 2003. “The neighborhood or the region? Untangling the density-productivity relationship using geocoded data.” *Centre of Excellence for Science and Innovation Studies - Working Paper Series.* Paper n. 318.o

Lucas, R. E.; Rossi-Hansberg, E. 2002. “On the internal structure of cities.” *Econometrica* 70 (4): 1445-1476.

McDonald, J. F. 1987. “The identification of urban employment subcenters.” *Journal of Urban Economics* 21: 242-258.

McMillen, D. P. 2001. “Nonparametric employment subcenter identification.” *Journal of Urban Economics* 50: 448-473.

Melo, P. C.; Graham, D. J.; Noland, R. B. 2009. “A meta-analysis of estimates of urban agglomeration economies.” *Regional Science and Urban Economics* 39 (3): 332-342.

Menezes, T.; Azzoni, C. 2006. “Convergência de salários entre as regiões metropolitanas brasileiras: custo de vida e aspectos de demanda e oferta de trabalho.” *Pesquisa e Planejamento Econômico* 36 (3): 449-470.

Mills, E. S. 1967. “An Aggregative Model of Resource Allocation in a Metropolitan Area.” *American Economic Review* 57 (2): 197–210.

Ministério do Trabalho e Emprego – MTE. *Relação Anual de Informações Sociais – RAIS e Cadastro Geral de Empregados e Desempregados – CAGED.* Brasília: MTE, SPPE/DES/CGET, 2010.

Mion, G., Naticchioni, P. 2009. “The spatial sorting and matching of skills and firms.” *Canadian Journal of Economics* 42 (1): 28-55.

Moretti, E. 2004a. “Estimating the social return to higher education: evidence from longitudinal and repeated cross-sectional data.” *Journal of Econometrics* 121: 175-212.

Moretti, E. “Human capital externalities in cities.” In Henderson, J. V.; Thisse, J.F. (Eds.), *Handbook of Regional and Urban Economics.* Amsterdam: Elsevier, 2004b.

Muth, R. F. *Cities and Housing.* Chicago: University of Chicago Press, 1969.

Overman, H. 2004. "Can we learn anything from economic geography proper?" *Journal of Economic Geography* 4: 501–516.

Roca, J. D. L.; Puga, D. 2017. "Learning by working in big cities." *The Review of Economic Studies* 84 (1): 106–142.

Rocha, R. M. Silveira Neto, R. M.; Gomes, S. M. F. P. O. 2011. "Maiores cidades, maiores habilidades produtivas: ganhos de aglomeração ou atração de habilidosos? Uma análise para as cidades brasileiras." *Revista Econômica do Nordeste* 42 (4): 675-695.

Rosenthal, S. S., Strange, W. C. 2003b. "Evidence on the nature and sources of agglomeration economies." *Handbook of Regional and Urban Economics* 4: 2119-2171.

Rosenthal, S. S., Strange, W. C. 2003a. "Geography, industrial organization and agglomeration." *Review of Economics and Statistics* 84: 377-393.

Rosenthal, S. S.; Strange W. C. 2008. "The attenuation of human capital spillovers," *Journal of Urban Economics* 64: 373–389.

Silva, D. L. G. 2018. "Contribuição dos efeitos de firma e de indivíduos para os efeitos de localização sobre os salários e para a variação salarial do trabalhador formal do Brasil." *Pesquisa e Planejamento Econômico* 48 (2): 7-37.

Silva, D. L. G. *Economias de aglomeração e heterogeneidade de trabalhador e firma na determinação de salários no Brasil.* PhD Dissertation presented to Economics Department, University of São Paulo. São Paulo, 2017.

Silva, D. L. G. Santos, G. F.; Freguglia, R. S. 2016. "Distribuição espacial dos efeitos de aglomeração sobre os retornos à educação no Brasil entre 1995 e 2008." *Pesquisa e Planejamento Econômico* 46, (2): 7-46.

Storper, M.; Venables, A. J. 2004. "Buzz: face-to-face contact and the urban economy." *Journal of Economic Geography* 4 (4): 351–370.

Van Soest, D., Gerking S.; Van Oort F. G. 2006. "Spatial impacts of agglomeration externalities," *Journal of Regional Science* 46: 881–899.

Yankow, J. J. 2006. Why do cities pay more? An empirical examination of some competing theories of the urban wage premium. Journal of Urban Economics, 60: 139-161.

Woodcock, S. 2015. Match effects. Research in Economics, 69:100-121.

Woodcock, S. 2008. Wage differentials in the presence of unobserved worker, firm, and match heterogeneity. Labour Economics, 15: 771-793.

Wred, M. A. 2015. Continuous spatial choice logit model of the polycentric city. Regional Science and Urban Economics, 53:68-73.

Appendix

Table A1 - Mobility of Workers and Firms

	Obs.	%
Firms' Mobility		
Across cells	11,345	10%
Total of Firms (yearly)	112,400	100%
Employee's Mobility		
Across firms	53,268	11%
Across cells	60,277	13%
Total of employee (yearly)	381,785	100%

Source: own elaboration based on RAIS data.

Table A2 - Employment density by cell size

Cell size	Mean	Std. Dev.	Min	Max	Employment Density (Mean by 1 km²)
0.5 km²	6,407	8,014	1	58,536	12,814
1 km²	10,671	14,104	1	57,773	10,671
2 km²	18,329	21,830	0	31,417	9,164
4 km²	33,165	38,779	1	210,337	8,291

Source: authors elaboration based on RAIS data.

Table A3 - Intra-urban wage premia at Different Geographic Scales

	POLS I	POLS II	POLS III	POLS IV	POLS V	FE I	FE II	FE III	FE IV
0.5 Km²									
Density	0,3801***	0,2607***	0,1088***	0,0982***	0,0241***	0,0105***	0,0136***	0,0065***	0,0112***
R^2	0.04	0.54	0.77	0.77	0.79	0.96	0.87	0.96	0.96
2 Km²									
Density	0,0729***	0,0494***	0,0237***	0,0211***	-0,0017***	0,0020***	0,0021***	0,0016***	0,0112***
R^2	0.02	0,53	0,77	0,7711	0,79	0,96	0,87	0,96	0.96
4 Km²									
Density	0,0393***	0,0221***	0,0128***	0,0117***	0,0021***	0,0017***	0,0019***	0,0016***	0,0085***
R^2	0.03	0.52	0.77	0.77	0.79	0.96	0.87	0.96	0.96
Controls	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummy	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality dummy	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Cell dummy	No	No	No	No	Yes	No	No	No	Yes
Individual FE	No	No	No	No	No	Yes	No	Yes	Yes
Firm	No	No	No	No	No	No	Yes	Yes	Yes
Obs.	4,573,205	4,573,205	4,573,205	4,573,205	4,573,205	4,573,205	4,573,205	4,573,205	4,573,205

Source: authors elaboration based on RAIS data. Note: Cells of 1 km^2. The specifications that include controls take tenure, $tenure^2$, education, firm specialization, and municipality dummies. The POLS specification includes additional controls for gender, age, age^2 and the firm's sector of activity. Significance: 1% (***), 5% (**) and 10% (*). Standard error adjusted for individual clusters. We use the total number of employee in the cell divided by cell size to identify internal density.

Table A4 - Kernel Functions, AIC criteria and Optimal Bandwidth

	Gaussian		Bisquare		Tricubic	
Year	AIC	Bandwidth (Km)	AIC	Bandwidth (Km)	AIC	Bandwidth (Km)
2002	150,453.9	0.910	150,289.6	2.271	150,197.6	2.309
2003	151,015.5	0.901	150,902.8	2.214	150,763.0	1.991
2004	152,529.7	0.886	152,384.9	2.160	152,233.8	1.979
2005	154,075.7	0.905	153,929.3	2.218	153,810.6	2.095
2006	154,806.5	0.903	154,670.1	2.205	154,538.4	2.063
2007	158,084.3	0.911	157,947.1	2.236	157,831.5	2.105
2008	157,403.6	0.879	157,169.2	2.157	157,033.3	2.095
2009	157,891.6	0.869	157,671.1	2.131	157,522.1	2.023
2010	160,279.4	0.910	160,142.8	2.244	160,025.8	2.099
2011	159,271.1	0.859	158,985.5	2.089	158,823.2	2.038
2012	159,199.8	0.857	158913.1	2.079	158,750.4	2.038
2013	159,784.0	0.879	159,549.5	2.154	159,408.2	2.094
2014	159,668.7	0.871	159,429.8	2.129	159,279.6	2.063
Mean		0.888		2.176		2.076

Source: authors elaboration from RAIS data. Note: Cells of 1 km^2.

CONFLITO DE INTERESSE

Os autores declaram não terem quaisquer conflitos de interesse.

EDITOR-CHEFE

Dante Mendes Aldrighi

Professor - Department of Economics University of São Paulo (USP)