Estimating the Intra-Urban Wage Premium for a Metropolitan Area in a Developing Country

Rodger B. A. Campos[1]
Carlos R. Azzoni[2]

Abstract

We estimated the intra-urban wage premium and its attenuation effect with a balanced panel of workers in the metropolitan area of Sao Paulo, Brazil. We geocoded the employment data on a grid of 9,071 cells of 1 km² and compared wages in the adjoining cells. There is a lack of papers dealing with the agglomeration effects on wages in developing countries, especially focusing on a fine geographical scale, as we considered in this paper. The estimated intra-urban wage premium ranges from 0.83% to 1.12%, depending on the size of the cells (0.5, 1, 2, and 4 km²). The attenuation effect is observed but restricted to 3 km away from the inner cell and is stronger for non-educated workers.

Keywords: agglomeration, attenuation, intra-urban wage premia, central business district

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[1] Associate Researcher in the Regional and Urban Economics Lab at the University of São Paulo rodgercampos@hotmail.com
[2] Professor of Economics, University of São Paulo cazzoni@usp.br

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). 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. It is composed of 39 municipalities spread over an area of 7,946 km². Its population in 2017 was 21.6 million, representing 10% of the country's population. The municipality of São Paulo, the state's capital, accounts for 56% of the population in the area[3].

It is important 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 for 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 questions that come up are these: How local are the agglomeration effects, and how far 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; Haddad and Barufi 2017; Silva, 2017, 2018). Even controlling for regional cost of living and other variables, the wage inequality across metropolitan areas persist (Azzoni and Servo 2001; Menezes and Azzoni 2006; Galvao et al. 2016).

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 Brazilian Ministry of Labor that includes interesting details of workers and firms, including their addresses. We have assembled a 13-year balanced panel in which each worker and firm is precisely located in the metropolitan space. With this database, we move forward to the identification of the intra-urban wage premium and its attenuation in the metropolitan area. Contrary to the typical result of between-city agglomeration effects studies, which come up with one sole coefficient for each city, we are able to identify the within-city wage premium and assess how unequal it is in the metropolitan area.

Density was calculated for cells of 0.5 km², 1 km², 2 km², and 4 km², to explore the modifiable areal unit problem (MAUP), well known in the empirical literature. To make sure 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 headquarters. Following Combes, Duranton, and Gobillon (2008), we estimate the elasticity of wage with respect to employment density. We do this first by ignoring the neighborhood, to compare our findings with the empirical literature. As in Rosenthal and Strange (2008), we then control for the neighboring cells in the estimation of 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 more educated workers. 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 on the within-city wage-premium and its attenuation. Section 5 separates the analysis by education level, and Section 6 concludes.

[3] Even São Paulo Metropolitan Area is the greatest one in Brazil and host the fifth greatest city in the world, our decistion to select this region is related to budget constraint to geocode RAIS database. Furthermore, many studies have evaluated agglomeration effects in a regional scale (municipalities, labor area, etc.), but we bring the intra-urban perspective of analysis that is a step ahead in the empirical literature in the developing countries.

2. Literature Review

Many studies have pointed to the wage differential in large urban centers (Ahlfeldt and Pietrostefani 2019). There are three sources of this spatial wage heterogeneity: 1) differences in the composition of the labor market, reflecting the skills of the necessary workers; 2) differences in endowments, such as in climate; and 3) interactions among workers and/or firms (Combes, Duranton, and Gobillon 2008). Sharing, learning, and matching are the mechanisms that activate the economies of agglomeration and increase productivity (Duranton and Puga 2004). Places with employment density and workers' productivity attract more skilled workers, more productive firms, and accelerate both the stock of human capital and wage growth (Glaeser and Maré 2001).

Even though disentangling sharing, learning, and matching is yet to be properly achieved, empirical findings on urban wage premia have been provided, ranging between 1% and 11% (Costa and Overman 2014), with an average 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 area, etc.), 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 (2003), van Soest, Gerking, and van Oort (2006), Rosenthal and Strange (2008), and Andersson, Klaesson, and Larsson (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 to reach a better understanding of 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 have moved forward by overcoming this condition. Van Soest, Gerking, and van Oort (2006) measured the extent to which agglomeration economies in one location contribute to employment and establishment growth at the other locations in one province of the Netherlands. They show that agglomeration economies positively affect the outcome variables, but their effects are sharply reduced with distance. Rosenthal and Strange (2008) estimated the relationship of agglomeration and proximity to wages in the US 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, Klaesson, and Larsson (2016) studied wage levels and density in grids of 1 km² cells for selected places in Sweden over a 20-year period, using the first- and second-order neighborhoods to identify the attenuation effects.

Although this latter study represents a step ahead in the analysis of the within-city agglomeration economies, these scholars' database did not permit them to control for individuals' and firms' nonobserved 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.) in comparison to cross-section results (Glaeser and Maré 2001). Yankow (2006) found premia between 8% and 19% without controlling for nonobserved individual skills, and only between 3.3% and 5% when those are controlled for. Workers' skills are associated with firms' size (Mion and Naticchioni 2009) and disregard worker self-selection results in an important omitted variable problem, which overestimates the results (Combes, Duranton and Gobillon 2008). Firms' nonobserved characteristics are also important for controlling firms' sorting (Abowd, Kramarz, and Margolis 1999). As different firms and individuals may benefit differently from the spatial labor market, the estimation demands a suitable database do identify such sorting.

[4] These places are labeled central business districts in monocentric cities, or subcenter business disctricts in polycentric cities. See Alonso (1964), Mills (1967), Muth (1969), and Brueckner (1987) for a general theoretical model.

Having these issues in mind, we seek to 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 for the selection of the neighborhood and explore higher orders of the neighborhood as well.

3. Methodology and Database

3.1. The model

The objective is to estimate the wage premium of working in a dense area, and its attenuation with distance. We use the econometric specification of Combes, Duranton, and Gobillon (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

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

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 $\psi_j$are worker and firm fixed effects; and $\epsilon_{i,t}$ is the error term, assumed iid.

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

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

where $A_{c,t}^{l}$ is job density in cell c at time t, l represents rings of expansion around cell c ($l = 1, 2, \dots, L$), 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, ρ_3 … ρ_l capture the attenuation effect. If $\rho_1 > \rho_2 > \rho_3 > 0$ and is 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 at all.

One critical issue is the selection of rings. Unlike Rosenthal and Strange (2008) and Andersson, Klaesson, and Larsson (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

$$A_c = \beta_0(u_c, v_c) + \varepsilon_c \tag{3}$$

where A_i is the number of employees in cell c, (u_c, v_c) are 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

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

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

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 nonparametric estimator for continuous localization functions (u_c, v_c) using kernels and the log-likelihood for each set of estimates, and it does not provide a single solution. The way to adjust the optimization is to consider local log-likelihoods and take observations close to the cell c (Bowman and Azzalini 1997; Fotheringham, Brunsdon, and Charlton 2002). Thus, the estimation of GWR involves the selection of bands (or windows) for an isotropic kernel spatial weight function, such as the Gaussian, tricubic, and quadratic functions, for example. The size of the windows is based on the Akaike information criterion (AIC) minimization method (Fotheringham, Brunsdon, and Charlton 2000). Since the AIC approach 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 for a set of fixed effects, there might be unobserved workers' ability or firms' sorting that would be embodied in the error term $\epsilon_{i,t}$ (Equation 5). To control for endogeneity, geology variables (Combes et al. 2008) and Bartik instrumental variables (Silva 2017) have been used as instruments. 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. 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 for employment located at outer rings, as in Rosenthal and Strange (2008).

3.2. Database

The data set comprises a balanced panel of workers covering the period 2002–2014. Each legally established firm must provide the Ministry of Labor with annual information regarding their employees.[6] 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.[7]

Our database contains 18–65-year-old individuals working more than 20 hours per week in a private firm. For workers with more than one labor contract, we have selected the one with the highest wage. The panel data is composed of 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 of 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 (mix of activities in each cell). Employment density (number of jobs per km^2) is the key variable. Since we use same-size cells of 1 km^2 as the geographical units, there are no problems related to distinct area sizes, nor are there gross and net employment density problems (Ciccone and Hall 1996; McDonald 1987, McMillen 2001). Figure 1 shows the grid of cells.

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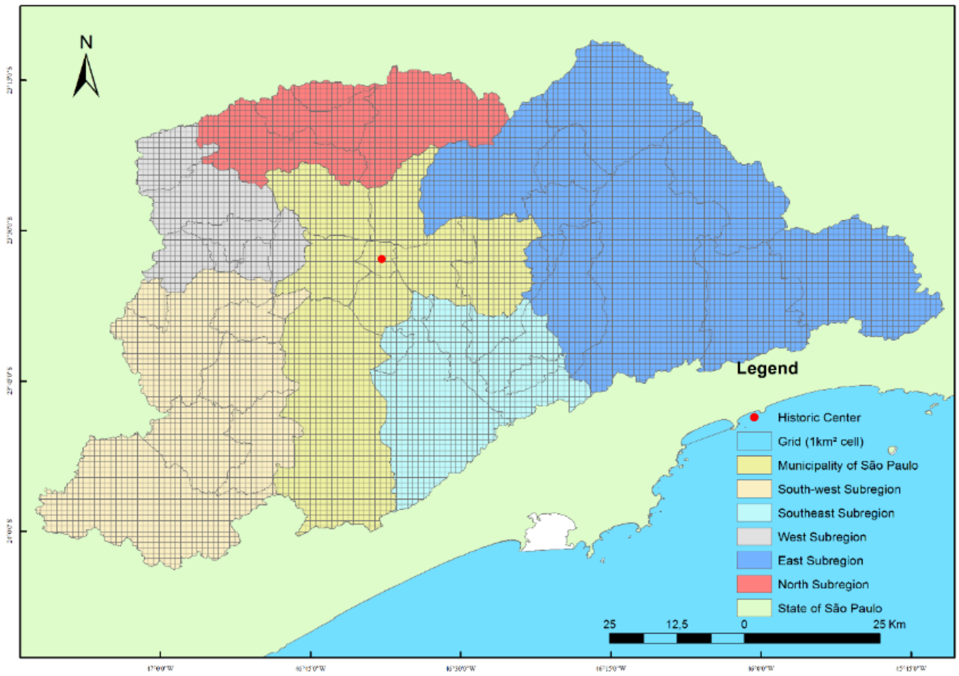
[6] RAIS (Relação Annual de Informações Sociais) is a report compulsorily requested to formal establishments (public and private). Firms must complete the report annually, and the Ministry of Labor is responsible for managing the information. It covers only formally established (incorporated) organizations (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.
[7] 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.

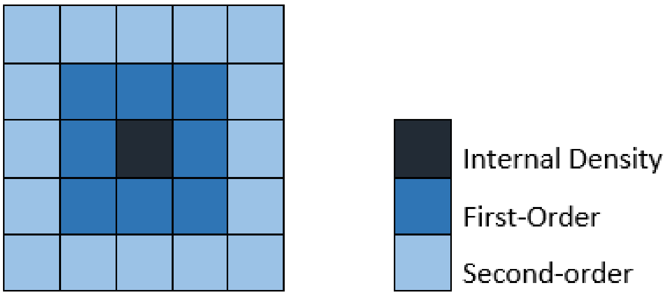
Figure 1: Metropolitan Area of São Paulo, Square Cells of 1 km²



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 cell ($l = 1$), 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 pertaining to 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 noncategorical variables. Hourly wages were properly deflated.[8] 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 located in São Paulo city (capital of the state), Barueri city, and the ABCD region. As shown in Table 1, the variance of density 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. As Table A2 in the Appendix

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

shows, 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.

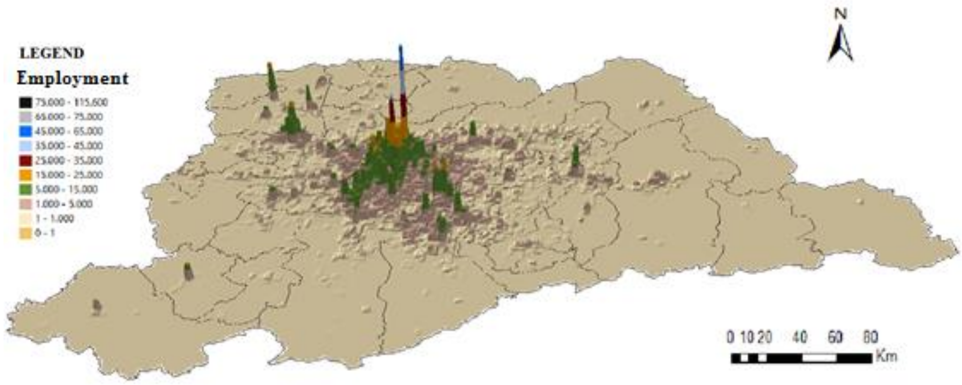
Table 1: Descriptive Statistics of the Noncategorical Variables

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 (W Density)	7,235	7,815	0	44,642
Second-order density (W2 Density)	6,112	5,954	0	26,821
Tenure (month)	111.24	83.26	0	598.9
Tenure²	19,307	26,516	0	358,681
Age (year)	39.10	9.05	18	65
Age²	1,610	731	324	4,225
Specialization Index	1	1.13	0.0001	14

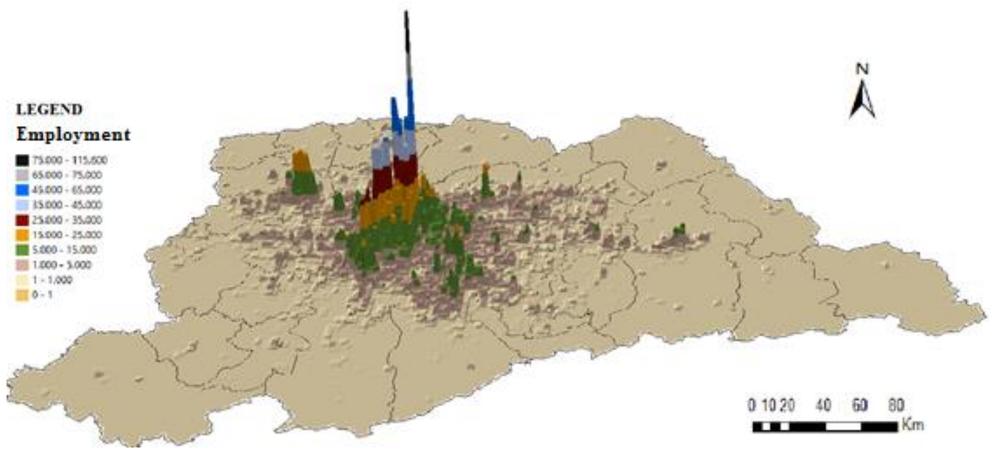
Source: Authors' elaboration based on RAIS data.

Figure 3: Spatial Distribution of Jobs

2002



2014



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 interpreted as 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, and 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 those high-skilled workers who self-select to work in dense areas, for example. The identification of workers' fixed effects comes from the movement of workers between jobs and firms moving across cells. It is recognized that the movers may not be representative of all workers and firms and that the movements are not randomly decided. Given data limitations, using fixed effects is the best we could do to reduce the wage premium 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 is well-known, productive firms are also attracted to dense cells, and such self-selection demands controlling for sorting. In column FE II we remove worker and include firm 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 take that into account, we keep worker and firm fixed effects and add cell fixed effects, and come up with a wage premium of 1.02% (last column). The increase in the density effect is related to those unobservable characteristics that contribute to attract firms and/or workers to a cell but are not related to sorting, such as spatial vocation for certain types of business, etc. It is interesting to highlight that 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. The meta-analysis of 28 studies presented by Ahlfeldt and Piestrostefani (2019) indicates an average wage-density elasticity of 5% percent, with a standard deviation of 4%, and the average productivity-density of 8%, with a standard deviation of 4%. Andersson, Klaesson, and Larsson (2016) find results between 0.72% and 0.83%, without controlling for fixed effects. Our results indicate an intra-urban wage premium smaller 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 are tenure, $tenure^2$, education, firm specialization, and municipality dummies. The POLS specification includes additional controls for gender, age, age^2, and firm's sector of activity. Significance: 1% (***), 5% (**), and 10% (*). Standard error adjusted for individual clusters.

How sensible are the last results when the cell size changes? This question is not stressed in the empirical literature due to data limitations, but we can check the sensibility 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 km² cells is 1.12%, just above the 1.02% found for 1 km² cells, presented before. For 2 km² cells, the elasticity is half the value for 0.5 km² cells, and the value increases for 4 km² cells. This pattern is in line with Andersson, Klaesson, and Larsson (2016), confirming that smaller areas provide higher wage premia. Denser areas facilitate the sharing of knowledge and the other effects related to interactions, as 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 to 1 km²)
0.5 km²	Coeff.	0.3801***	0.0241***	0.0112***	12,814
	R^2	0.04	0.79	0.96	
1 km² [(b)]	Coeff.	0.1766***	-0.0105***	0.0102***	10,671
	R^2	0.03	0.79	0.96	
2 km²	Coeff.	0.0729***	-0.0017***	0.0056***	9,164
	R^2	0.02	0,79	0.96	
4 km²	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 3. [(b)] From Table 3.

5. Attenuation Effects

Urban economics models usually take the central business district (CBD) as a reference point in the estimation of wage gradients. Since we do not have any specific anchor, we compare the wage levels in the inner cells with the levels 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. But as the distance increases, we might approach another dense cell, and the wage level will increase because of 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 the GWR approach to estimate local means of employment concentration by using subsamples.[9] 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 associated distance based on the AIC. The tricubic kernel function minimizes the AIC criteria for all years and 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 as 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 log) of the inner cell of adding 100,000 new workers in that cell or in 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. An addition of 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 and are 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

[9] This approach is also used to identify subcentrality business centers (McMillen and Mcdonals (1997); McMillen (2001); Redfearn (2007))

effects spill over 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 not significant. 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, and firm specialization controls as well as time, municipality, cell, individual, and firm fixed effects. Standard error adjusted for individual clusters.

If we restrict the distance to 2 km, the attenuation in the wage premium is paramount, in line with the canonical models of urban economics and with the results of Andersson, Klaesson, and Larsson (2016). In the remaining columns of Table 4, we add more rings around the inner cell and observe their effects on the results. The coefficients for the wage premium in the inner cell are quite similar in the additional columns, and so is their attenuation in the first two rings. However, as more cells are added, their 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 increase, 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; Wrede 2015; Ahlfeldt et al. 2016). On the other hand, the selection of the bandwidth based on GWR proved to be adequate, providing an adequate isotropic area to measure the attenuation effect.

As the maps showing the distribution of jobs in the metropolitan area indicate, three subcenter business districts are present in the area.[10] We now perform an exercise just with the cells on those areas and estimate the attenuation effect involving all cells. As the results in the upper part of Table 5 show, the wage premium in the inner cell is similar to the ones shown in the previous table (between 0.055 and 0.07), and the attenuation is present beyond the second ring of cells, up to the seventh ring (column VIII). Thus, if we consider only the relevant cells in the area, based on employment density, 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, but we include all cells to measure attenuation. As can be seen in the lower part of Table 5, in this case, the spatial pattern of attenuation is not observed. The wage premium itself is only present in three columns, at 10% significance only. This indicates that multiple business centers influence the attenuation effects, and the direction of the rings' expansion matters for the analysis. When the rings expand from the CDB outward, the wage premium and the attenuation effect are clear.

[10] Campos and Azzoni (*forthcoming*) have determined the existence and extension of such centers in the metropolitan area.

Table 5: Wage Premia Attenuation from the Dense Cells

	I	II	III	IV	V	VI	VII	VIII	IX	X
Cells in the SDB only, attenuation to all cells										
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
Obs.	1,530,924	1,530,924	1,530,924	1,530,924	1,530,924	1,530,924	1,530,924	1,530,924	1,530,924	1,530,924
Cells outside the SDB only, attenuation to all cells										
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
Obs.	556,667	556,667	556,667	556,667	556,667	556,667	556,667	556,667	556,667	556,667

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 as well as time, municipality, cell, individual, and firm fixed effects. 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), but 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 when 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 in general relative to high-skilled workers. In this sense, the benefits generated by agglomeration, which stimulates the flow of knowledge and information, is relevant for workers and firms to whom such a flow matters the most (Moretti 2004a, 2004b; Bathelt, Malmberg, and Maskell 2004; Stoper and Venables 2004; Rosenthal and Strange 2008; Boulolod, Blum, and Strange 2010; Andersson, Klaesson, and Larsson 2016).

The discussion of human capital in this subsection is limited to workers' heterogeneity in terms of educational attainment. Although there certainly are other elements to human capital (Bacolod, Blum, and Strange 2009), education is a relevant component (Winters 2013). We run separately two regressions for workers with less than college education and with college education 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 1.4 times larger than workers with less than college, although these workers also benefit from agglomeration, but with less intensity. If density doubles, a worker without college gets a 0.8% wage increase, which is 22% lower than the average shown in Table 2. For a worker with college education, the wage increase is 1.16%, which is about 8% larger than shown in Table 2. Compared to the estimates of Andersson, Klaesson, and Larsson (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.

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: 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 as well as time, municipality, cell, individual, and firm fixed effects. Significance: 1% (***), 5% (**), and 10% (*). Standard error adjusted for individual clusters. Note2: For FE I and FE III, we use log–log functional forms, while for FE II and FE IV we use log-linear functional forms.

As the surrounding cells are included in the computations, columns FE II and FE IV show 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 a sharp decay in wages as the distance increases. As for educated workers, no attenuation is observed, indicating that the wage premium for such workers has a wider geographic scope, while low-skilled workers are spatially restricted to the internal ring.

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 the period 2002–2014, dispersed in a fine grid of 1 km *x* 1 km cells. The application to a major city of a developing country and the detailed geographical scale are important novelties of the study. We do not impose exogenously the central business centers (CBDs) or subcenters (SBDs), but we estimate the wage premium for each cell and for layers of surrounding cells. Based on the wage premium estimated in these three layers, we were able to 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 nonlinearity between the cell size and the 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 located up to 2 km of distance from the inner cell. We experiment with larger distances and find that beyond 2 km the wage premium might increase or decrease, without a clear pattern. This is related to the possibility of getting closer to other dense cells as distance increases, since the grid is highly detailed. An exercise in selecting only cells pertaining to the denser areas, but including all areas to evaluate attenuation, indicates that the typical result obtained in studies that use the CDB as a point of reference is replicated.

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 college education obtain just 58% of the educated workers' premium.

In addition to the main aims of this research, this study also sheds light on multiple business center issues. In contrast to traditional models that consider a monocentric city, we discuss the role of multiple business centers for the attenuation effect and the degree of localness in terms of the productivity spillover. Due to high density in the business centers, it affects workers' productivity (here measured by hourly wage) when the distance from inner cells is increased. These results support the conclusion that São Paulo metro is more likely to have characteristics of multiple-center cities than traditional monocentric cities. If neighborhoods more than 2 km of distance away from the inner cell are considered, our results are not in line with Andersson, Klaesson, and Larsson (2016) and Rosenthal and Strange (2008). However, restricting the analysis to 2 km around the inner cell, our results for the attenuation effects are in line with those studies.

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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 employees (yearly)	381,785	100%

Source: Authors' 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									
Internal 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									
Internal 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									
Internal 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 firm's sector of activity. Significance: 1% (***), 5% (**), and 10% (*). Standard error adjusted for individual clusters. We use the total of employees 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.