**Regional Inequality In The Wage Distribution Adjusted By Purchasing Power: Evidence From Brazilian Metropolitan Regions**

**Rodrigo Carvalho Oliveira[[1]](#footnote-1)**

**Raul da Mota Silveira Neto[[2]](#footnote-2)**

**Resumo**

Apesar da recente década de convergência de renda (Silveira Neto e Azzoni, 2012; Oliveira e Silveira Neto, 2016), a desigualdade de renda regional no Brasil ainda é alta e coexiste com um persistente desbalanceamento de bem-estar entre as regiões Sudeste e Nordeste. Tradicionalmente, pesquisadores e formuladores de políticas públicas que buscam compreender a desigualdade regional no Brasil enfatizam dois tipos de fatores explicativos, por um lado a concentração espacial das atividades produtivas e o papel da estrutura produtiva, e por outro as diferenças regionais nas características produtivas dos trabalhadores. O objetivo deste artigo é apresentar novas evidências sobre as fontes explicativas da desigualdade regional de renda em toda a distribuição dos rendimentos considerando os diferenciais regionais de custo de vida. Esta pesquisa possui duas contribuições. Primeiro, este é o primeiro trabalho que analisa a desigualdade regional de rendimentos ajustado pelo custo de vida em uma estrutura de decomposição Oaxaca-Blinder. Segundo, a abordagem aqui adotada permite uma decomposição detalhada dos efeitos composição e estrutura salarial em toda a distribuição dos rendimentos e, portanto, pode trazer muito mais informações que outras decomposições. O conjunto de evidências indica que a desigualdade regional varia bastante entre quantis e regiões. Nossos resultados indicam que a desigualdade regional é maior nos quantis superiores e que o nível de educação é o principal fator explicativo da desigualdade.

**Palavras Chave:** Desigualdade Regional. Brasil. Decomposição.

**Abstract**

Although the recent decade of regional income convergence (Silveira Neto and Azzoni, 2012; Oliveira and Silveira Neto, 2016), regional income inequality in Brazil is still very large and there is a persistent unbalanced well-being between southern and northern regions of the country. Traditionally, researchers and policy makers involved in understanding the resilient Brazilian regional income inequality emphasize two different kinds of factors supposed as the main responsible for the situation: the role of local productive structures and regional difference in workers individual characteristics highlighting the role of schooling. The objective of this paper is to provide new evidence about the sources of regional income inequalities in Brazil along the entire wage distribution taking into account the differentials of regional purchasing power. The research provides two important contributions. First, to the best of our knowledge, this is the first work that compares regional inequalities in an Oaxaca-Blinder decomposition type framework using wages adjusted for regional purchasing power differentials. Second, the approach allows a detailed decomposition of both composition and structure effects along the all wage distribution and, thus, can bring much more information than other decompositions. The set of evidence indicates that the regional wage gaps varies both across quantiles and northern metropolitan regions, even after adjusting for local price differentials. We found that the higher the quantiles of the wage distributions, the greater the regional wage gap: regional wage gaps are almost inexistent for lower quantiles and significant for the higher ones. The results also suggest that education is the main factor that explain the inequality.

**Keywords:** Regional Inequality. Brazil. Decomposition Techniques.

**1. Introduction**

Although the recent decade of regional income convergence (Silveira Neto and Azzoni, 2012; Oliveira and Silveira Neto, 2016), regional income inequality in Brazil is still very large and there is a persistent unbalanced well-being between southern and northern regions of the country. According to the most recent available information (for 2016), out of the 27 Brazilian states, the 15 Brazilian states with the lowest per capita GDP corresponded exactly to the 15 states of North and Northeast regions, and the economic disparities among them are also still significant, even considering the international experience. The per capita GDP of Maranhão state (in the Northeast region), for example, corresponded to only about 27% of the GPD per capita of São Paulo state (IBGE, 2018). Using satellite nightlight data and a sample of 180 countries, Lessaman and Seidel (2015) showed that Brazil belonged to the group of 25% countries with the highest regional inequality, confirming previous evidence provided by Shankar and Shah (2003). Given the country common language and culture, absolute factors mobility freedom, and strong tradition of regional policies, this situation continues to challenge researchers from regional science field.

Traditionally, researchers and policy makers involved in understanding the resilient Brazilian regional income inequality emphasize two different kinds of factors supposed as the main responsible for the situation. Inspired by the Brazilian historical economic development pattern based on exploration of spatially concentrated activities, Cano (1985) and Baer (2001) highlighted the importance of the spatial concentration of the Manufacturing sector for understanding Brazilian regional income unbalance, i.e., the authors highlighted the role of local productive structures. On the other hand, focusing on supply side factors, Pessoa (2000) and Ferreira (2004) argued that Brazilian regional income disequilibrium is fundamentally explained by regional difference in workers individual characteristics and highlighted the role of schooling. More recently, two other sources of income regional variation are highlighted by the literature. First, Silveira Neto and Azzoni (2011, 2012) showed that the public policy for the minimum salary and social programs that focused on the poorest families can substantially contribute to the dynamic of the country regional income inequality. Second, Barufi et al. (2017) showed that agglomerations gains play an important role in explaining Brazilian cities’ wage differentials. This contribution, thus, highlighted the potential role of the local returns to workers’ characteristics for understanding regional income differentials in Brazil.

Usually, empirical works that aims to explain the factors associated with regional income inequality consider decomposition strategies applied to individual income of different regions. The decompositions regularly follow the Oaxaca-Blinder approach (Blinder 1973, Oaxaca 1973) and try to estimate the contributions of individual and labor market characteristics (the so-called explained or composition effect) and of the returns to these characteristics (the so-called unexplained or wage structure effect) to regional difference of average income (Garcia and Molinam, 2002, Molleton et al. 2011, Duranton and Monstiriodis 2002, Pereira and Galego 2011, Vieira et al. 2006). Generally, these empirical works show that both local differences in workers’ characteristics and in the returns to these characteristics play important roles in explaining regional inequalities.

Recognizing the strong assumptions behind traditional Oaxaca-Blinder decomposition (ex. linearity) and that the spatial arbitrage capacity and the agglomeration gains can differently affect individuals according to their positions in the wage distribution, more recent investigations consider the regional inequality using reweighting approaches and decompositions through the entire wage distribution. For example, Motellon et al, (2011) applied Dinardo et al. (1996) reweighing strategy in order to create contrafactual distributions that allows studying and decomposing regional inequality in Spain through the wage distribution. Pereira and Galego (2014) applied the quantile-based decomposition method proposed by Machado and Mata (2005) and Melly (2005, 2006) to decompose regional wage differentials across the wage distribution in case of Portugal. Following the innovative strategy proposed by Firpo et al. (2009, 2011), Galego and Perreira (2014) and Herrera-Idárraga et al. (2016) considering, respectively, the cases of Portugal and Colombia, used reweighting and RIF (Recentered Influence Function) regressions in order to provide a detailed decomposition of both composition and structure effects along wage distributions, something not possible using previous techniques. The evidence provided by these studies confirms the existence of important variations in the level of regional inequality along the wage distribution.

As for the Brazilian case, these techniques were also applied and mixed results were obtained. Silveira Neto and Menezes (2008) applied traditional Oaxaca-Blinder approach to study regional inequality between Southeast (the richest) and Northeast (the poorest) regions and found that workers’ characteristics, mainly regional differential in schooling, is the main source of the Brazilian regional inequality. Similar results were obtained by Duarte et al. (2003) applying DiNardo et al. (1996) reweighing procedure. However, using Mata and Machado (2005) decomposition approach, Guimarães et al. (2006) found that the regional differences in the returns to workers’ characteristics (mainly the returns to education), i.e, the wage structure effect, is the main factors behind the Brazilian regional disparities and that these influence varied along the wage distribution. Finally, more recently, using the RIF regressions approach (Firpo et al. 2009), Oliveira and Silveira Neto (2016) found that both the workers’ characteristics, including schooling and the economic sector, and the returns to these characteristics matter for understanding Brazilian regional inequality. These authors also confirmed that both effects vary along the wage distribution with bigger regional income difference found in the lower income quantiles.

This set of applied empirical investigation about Brazilian regional income inequality is, thus, far from conclusive. Importantly, all these application share a substantive limitation: they consider only nominal wages and do not adjust values for regional purchasing power differentials. In the Brazilian case, this limitation is far from irrelevant even when comparing, for example, metropolitan regions (which attenuates regional price differentials). Actually, Almeida and Azzoni (2016) recently showed that while in 2014 the cost of living in the Brasilia Metropolitan Region is 14% higher the average cost of living of all 11 most important Brazilian metropolitan regions, for the Metropolitan Region of Fortaleza this cost was 19% lower. Considering then the same most important Brazilian metropolitan regions (MRs), these authors also obtained that, after taking into account regional purchasing power differentials, there was a reduction of 28% in the value of the Gini index for the per capita income distribution among these MRs. Notice that this limitation directly affects the shares of the contributions of individual and labor market characteristics (the so-called composition effect) and of the returns to these characteristics (the so-called unexplained or structure effect) in Oaxaca-Blinder type decompositions, making the results quite imprecise. Furthermore, these purchasing power differentials certainly are much greater when comparing macro regions, as proceeded by Guimarães et al. (2006) and Oliveira and Silveira Neto (2016), making their results quite imprecise.

The objective of this paper is to provide new evidence about the sources of regional income inequalities in Brazil along the entire wage distribution taking into account the differentials of regional purchasing power. More specifically, we use the recent regional purchasing power index provided by Almeida and Azzoni (2016) to adjust nominal wages of the Brazilian metropolitan regions and apply reweighting together with RIF regression (Firpo et al. 2009) to measure the contributions of different determinants of wages to the inequality between São Paulo metropolitan region (the richest one, a part from Brasília) and each of the metropolitan regions of the North (Belém) and Northeast (Fortaleza, Recife, and Salvador), the set of four poorest Brazilian metropolitan regions.

The research provides two important contributions. First, to the best of our knowledge, this is the first work that compares regional inequalities in an Oaxaca-Blinder decomposition type framework using wages adjusted for regional purchasing power differentials. Previous work of Menezes and Azzoni (2006) also use values adjusted for regional purchasing power differentials among metropolitan regions, but this only work considers these adjusted values for studying income convergence in growth regression exercises and it does not decompose the sources of regional inequality. Thus, we are able to correctly measure the shares of workers’ characteristics and of returns to these characteristics in explaining regional inequality among Brazilian metropolitan regions. Second, Oliveira and Silveira Neto (2016) is the only work that applies the RIF regressions approach (Firpo et al. 2009) and reweighting using 2010 Demographic Census. The approach allows a detailed decomposition of both composition and structure effects along the all wage distribution and, thus, can bring much more information than other decompositions. But, because their intention of comparing results across different census data, the authors only considered a few set of explanatory variables in the wage regressions (those compatible across decennial census). We apply the same strategy to a more recent data (Brazilian official household survey of 2014) that includes a much richer set of determinants of the wages, utilize a more precise measure of labor income (hourly wage), and consider only metropolitan regions. These aspects allows better controls for observables and non-observables covariates that may differently affect metropolitan, urban non-metropolitan, and rural environments. As there are significant regional income inequalities across rural areas in Brazil, these gains can also impose a limitation; however, as Brazil is a highly urbanized country (around 85% of its population living in cities), we believe that we are able to capture more rigorously a relevant part of Brazilian regional wage inequality.

The set of evidence indicates that the greater regional wage gaps varies both across quantiles and northern metropolitan regions, even after adjusting for local price differentials. We found that the higher the quantiles of the wage distributions, the greater the regional wage gap: regional wage gaps are almost inexistent for lower quantiles and significant for the higher ones. While individual characteristics (mainly the university degree) are the main factors associated with the regional wage inequalities for the intermediary and highest quantiles, no role for the spatial concentration of the Manufacturing or other economic activity was obtained.

The paper is structured through more four sections. In the following section, we briefly present the adopted empirical strategy. In section three, we present the data and preliminary evidence about wage disparities between São Paulo and the northern metropolitan regions. The results of the research are presented in section four and final remarks and conclusions in section five.

**2. Empirical Strategy**

In a standard Oaxaca-Blinder decomposition the overall inequality is split between the composition effect which explain the share of inequality by the difference in characteristics of individuals between the two groups, and the wage structure effect which explain the portion of inequality by the differences in return on the characteristics of similar individuals, but in different groups. In this study, we want to evaluate the difference in real labor incomes between each metropolitan region (Salvador, Recife, Fortaleza, and Belém) in relation to the metropolitan region of São Paulo. The composition effect will evaluate, for example, the wage inequality between regions explained by differences in observed characteristics, such as age and education. The wage structure effect will capture the differences of returns, such as return on education, for the wage inequality. It is necessary to emphasize that, although the results of the detailed decomposition of the composition and wage structure effects are based on correlations and cannot be interpreted as causal parameters, they document the quantitative relative importance of each factor in explaining regional income inequality. In this sense, it contributes to future analyses that seek to identify the causes of inequality and generates insights for designing policies that seek to reduce these disparities (Kilic, Lopez, and Goldstein, 2015).

Some methods tried to perform Oaxaca-Blinder related decomposition in the entire distribution of income (Machado e Mata, 2005; Melly, 2005, 2006; Dinardo, Fortin e Lemiex, 1996; Juhn, Murphy and Pierce, 1993). But, although they can decompose the inequality between the overall composition and wage structure effect, they don’t provide a way to compute the contribution of each covariate to the both effects (Fortin et al, 2011). Firpo, Fortin, and Lemieux (2007) proposed an Unconditional Quantile Regression that enables us to generalize the Oaxaca Blinder decomposition for any distribution measure, such as the mean, median, quantiles, variance, and Gini index.

Let F be a distributional statistic , where is the cumulative distribution function of variable Y, so is the influence of an individual observation on this distributional statistic. Subsequently, adding *υ*(*F*) back into the influence function produces what the authors call the “Recentered Influence Function” (RIF), which is their greatest contribution and what differentiates their work from other antecedents. The RIF decomposition has the property of being path independent, because the order in which the different elements of the detailed decomposition are calculated does not affect the decomposition results (Firpo, Fortin, and Lemieux, 2010), and its calculated as:

(1)

The RIF for the th quantile is given by:

(2)

Where is the sample quantile, is the marginal density at the point and is an indicator function indicating whether the value of the outcome variable is less than .

A very important property of this is the fact that the conditional expectation of the RIF is equal to the value of the statistic , a property that does not hold in a conditional quantile regression (Koenker and Basset, 1978). Chi and Li (2008) points out that the unconditional quantiles provided by the RIF method has the advantage of estimate the marginal effect of the covariates on the unconditional quantiles of interest using a linear regression model of the RIF on the covariates. So, we estimate the effects of the covariates on using a linear regression:

|  |  |
| --- | --- |
|  | (3) |

Here, each coefficient and are the approximate marginal effects of the explanatory variables on the wage quantile for workers. After estimating the RIF for each metropolitan region (RM) and for São Paulo (SP), we decompose the overall inequality ( between the Composition Effect ( and Wage Structure Effect (. Another important feature, as pointed out by Barsky et al (2011), is that when the conditional expectation of wages is nonlinear, a correction using some reweighting approach is necessary. However, this reweighting approach generates the specification error and the reweighting error. We decompose the wage inequality as:

(4)

Where:

(5)

and

+ () (6)

The index “c” means the counterfactual distribution of São Paulo. Fortin, Lemieux and Firpo (2011) explained that when the specification error equal to zero, the conditional expectation of wages is linear. The errors are shown in the Appendix (Table A1), and as can be seen, the specification error doesn’t have statistically significance, so they are not different from zero. Therefore, in our analysis we estimate the decomposition, without the reweighting procedure:

(7)

Where:

and (8)

(9)

It is also worth noting that a common problem of these decomposition methods is the invariance of the base group when calculating the wage structure effect (Oaxaca and Ransom, 1999). That is, when using categorical explanatory variables, the result of the estimation of the detailed decomposition varies depending on the base group chosen. In this case, in order to overcome this problem, we implemented the correction proposed by Yunn (2005) at the sectors dummies.

Several studies have already used RIF. Chi and Li (2008) analyze gender wage inequality in Chinese urban areas and conclude that the income differential has increased in China, and this increase has been higher in the lower quantiles. Firpo, Fortin, and Lemieux (2011) conclude that technological change has been responsible for much of the changes in wage distribution over the last three decades in the United States. Heywood and Daniel Parent (2012) analyze income inequality in black-and-white performance payments in the US and show that there is a tendency for inequality to increase as we move to the top of the income distribution. Medina (2013) shows that the wage structure effect is mainly responsible for wage differentials in Nicaragua. Ndoye (2013) concludes that return on education is the most important component in explaining disparities between rural and urban regions in Senegal that this effect increases as we move to the top end of the distribution. Kilic, Lopez, and Goldstein (2015) results indicate that women are on average 25% less productive than men in Malawi and that this differential is mainly explained by the composition effect.

Some applications of the decomposition using the RIF have already been also performed for Brazil. Salardi (2012) investigates the gender and race wage differences in Brazil in the last two decades. She finds that the wage structure effect is more important in explaining income differentials between genders than the composition effect. However, when analyzing racial differentials, the composition effect is more important. Brito, Machado, and Kerstenetzky (2013) argue that the minimum wage play a very important role in the evolution of income inequality in Brazil between 2001 and 2010. The authors find that the wage structure effect is more important than the composition effect in explaining the evolution of inequality between 2001 and 2011. More recently, Ferreira, Firpo, and Messina (2017) analyzed the fall in income inequality in Brazil between 1995 and 2012. The authors found that both the wage structure effect and the composition effect were important in explaining the fall in inequality in the period, in the order of 50 % each. Among the variables that most explain the wage structure effect, the authors find that education, economic activities, and experience are the most important, and while the first two factors contribute to a decrease in inequality, the latter contributes to an increase. When analyzing the detailed decomposition of the composition effect, the authors identified a strong weight of experience and education in explaining inequalities.

Using the specification of equation (3) applied to cross section database from Brazilian metropolitan regions obviously brings worries about endogeneity, since some observable variables are potentially associated with non-observable factors that affect individual productivity (Card, 1999; Hout, 2012). Furthermore, spatial sorting by the individuals across Brazilian cities also represents a potential source of bias, once more skilled individual may choice cities with higher returns to individual abilities. Actually, both problems appear present in Brazilian labor market. Teixeira and Menezes-Filho (2012), for example, showed that returns to education drops when using instrumental variables for schooling levels, and Freguglia and Menezes Filho (2012) showed that controlling for individual fixed effects brings an important reduction in Brazilian regional income disparities. However, we believe that these potential problems are strongly attenuated and do not substantively affect our decomposition results. Firstly, different from Freguglia and Menezes Filho (2012), we are considering only metropolitan regions, which turns compared environments much more similar. These environments tend to attack similar kind of individuals and present the more similar types of occupation within sectors. Secondly, we use a significant number of explanatory variables (individual and labor market characteristics), which makes the influence of non-observable factors less important. Thirdly, as indicated by Firpo et al. (2018), even if the estimative of coefficients are not necessarily unbiased, since the different sources of biases act in the same ways in the matched environments (a situation that is much more probable when comparing metropolitan regions), it is possible to obtain a credible estimative for the wage structure effect (a contra factual estimative of the individual wage in a regional different context). These two last points turn the Teixeira and Menezes-Filho (2012) worry much less important. Finally, in spite of these considerations, as causality is not assured, we do not interpret the estimative of the coefficients of the regressions as causal marginal effects of the variables, but as indicators of the degree of association between them and the dependent variable.

**3. Data description and introductory analysis**

We use data from the official annual household survey for the year of 2014, specifically, the information comes from the *Pesquisa Nacional por Amosta de Domicílio* (PNAD) provided by IBGE (Instituto Brasileiro de Geografia e Estatística*)*. Although all the information are also available for more recent years (up to 2017), nominal values can only be adjusted for local purchasing power using the indexes generated by Almeida and Azzoni (2016) until the year of 2014. The PNAD is a traditional and very rich database and includes both household and labor market information. These informations are available for all 27 Brazilian states and the 10 most important metropolitan regions. As the local price indexes provided by Almeida and Azzoni (2016) are available only for metropolitan regions, we consider information only for the metropolitan region of São Paulo (the biggest and most developed one) in the Southeast region and for metropolitan regions of Belém (in the North region) and Salvador, Recife, and Fortaleza (in the Northeast region) [[3]](#footnote-3). These last four metropolitan regions are not only the ones located in the North part of the country, but also the Brazilian poorest metropolitan regions among the ten aforementioned.

For this set of five metropolitan regions, we obtain information about variables commonly used in Mincer type equations. Our dependent variable is the log. of real hourly labor income and it is measured after adjusting nominal hourly labor income from PNAD using Almeida and Azzoni (2016) purchasing power differentials among Brazilian metropolitan regions. The set of explanatory variables includes individual (experience, schooling, race, family size, and civil status) and labor market characteristics (formal/informal occupation and economic activities). The sample is composed by individuals from 10 to 65 years old with positive labor income and occupied in non-agriculture activities. Using the sample weights, this set of observations corresponds to 8,429,703 individuals living and working in one of the five metropolitan regions.

In the following Figure 1, we order the 10 metropolitan regions of PNAD from the richest to the poorest and present both nominal monthly labor income and purchasing power differentials relative to the averages of all metropolitan regions using information, respectively, from PNAD and Almeida and Azzoni (2016). The information illustrates the fact that the richest metropolitan regions also present higher prices. For example, while the metropolitan region of São Paulo presents average labor income and local price are 23.4% and 6.0% higher than their respective averages for all metropolitan regions, in the metropolitan region of Fortaleza (the poorest one) labor income and prices are 39.2% and 19.0% lower than their respective averages for all metropolitan regions. Notice more specifically that, while the numbers of Figure 1 highlight the still substantive nominal labor income regional dipartites among Southeast-South and Northeast-North Brazilian metropolitan regions, they also indicate that regional price differentials are significant and should not be ignored when evaluating effective regional income disparities. This aspect is almost totally ignored in the studies of Brazilian regional inequalities due to the lack of information about regional price differentials.

Figure 1 – Labor Income and purchasing power (PP) differentials relative to average values (%)

– Brazilian Metropolitan Regions – 2014.

Table 1 presents descriptive statistics of the variables we used. Three important facts about wage differentials should be highlighted. First, we notice that an important part of mean wage differentials of the northern metropolitan regions relative to São Paulo metropolitan region is explained by regional cost of living differentials. For men and considering the average across northern regions, about 52% of mean wage gap can be attributed to the regional differentials of costs of living, a portion that even greater for women (about 59%). However, because nominal differentials are so high, as can be noted from the second line of Table 1, regional real wage gaps relative to São Paulo remain generally substantive even after the adjustment for regional costs of living differentials. For example, the mean wage in São Paulo metropolitan region is about 35% higher than mean wage for Belém metropolitan region after taking into account the costs of living differentials between them. Actually, the real wage gap relative to São Paulo ranges from 18.5% (for Recife and Salvador) to 35%, in case of men, and from 9.4% (for Recife) to 20.9% (for Fortaleza), for women. This illustrates the third point about regional wage differentials: generally, they are higher for men than for women. Specifically, while average wage nominal and real differentials are, respectively, around 55% and 26% for men, the correspondent gaps are around 41% and 16% for women.

This last point is perfectly consistent with the lower regional schooling differentials across the metropolitan regions for women, as can be noted in Table 1 though the percentages of workers with high school and college degrees. However, in spite of smaller regional differential for other levels of schooling, we noticed that there are still significant regional schooling differentials associated with university degree. For example, while around 21.7% of men workers living São Paulo metropolitan region had a college degree, this percentage was just 9.3% in Fortaleza metropolitan region. Notice also that, although there are not substantial regional differentials associated with other personal characteristics, regional differentials by race are very large; the percentages of black workers in Salvador metropolitan regions (above 80%), for example, are more than twice those found for SP metropolitan region.

But there are also substantial regional differences between São Paulo and the Brazilian northern metropolitan regions related to labor market structure. Reflecting Brazilian historical pattern of concentration of Manufacturing activities in the Southeast, the numbers of Table 1 indicate a much higher percentages of men and women working in the Manufacture sector in São Paulo when compared to Brazilian northern metropolitan regions. On the other hand, Public Sector employment is much more relatively frequent in Brazilian northern metropolitan regions; specifically, for example, while only 4.5% the men workers are in the Public Sector in São Paulo metropolitan region, the percentage amounts to 9.5% in Recife metropolitan region. Finally, the numbers of Table 1 also indicate a more formal labor market in São Paulo than in Brazilian northern metropolitan regions. Informality is particularly higher for women and in the metropolitan regions of Fortaleza and Belém.

Interestingly, although we consider only metropolitan regions (ignoring regional urban non-metropolitan and rural differentials), the numbers of Table 1 indicate considerable variation both in individual and labor market characteristics between São Paulo and the Brazilian northern metropolitan regions. As traditional explanations for Brazilian regional disparities rely on the contribution of different kinds factors associated with these characteristics, the current focus on metropolitan regions still allows verifying which of them are supported by the empirical evidence.

**Table 1 - Statistics descriptive – Brazilian metropolitan regions - 2014**

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Variables | São Paulo | | Salvador | | | Recife | | | Fortaleza | | Belém | |
| M | W | M | W | | M | W | | M | W | M | W |
|  |  |  |  |  | | Average values | | |  |  |  |  |
| Nominal wage | 3.81 | 3.69 | 3.44 | 3.34 | | 3.42 | | 3.38 | 3.25 | 3.24 | 3.39 | 3.45 |
| Real wage | 3.75 | 3.64 | 3.58 | 3.47 | | 3.58 | | 3.55 | 3.46 | 3.45 | 3.45 | 3.50 |
| Age | 35.82 | 34.94 | 36.23 | 35.37 | | 36.63 | | 35.84 | 34.52 | 33.97 | 36.11 | 36.99 |
| Experience | 19.24 | 17.34 | 20.39 | 18.91 | | 20.71 | | 18.20 | 19.27 | 16.97 | 20.32 | 19.44 |
| Family size | 3.41 | 3.33 | 3.19 | 3.00 | | 3.35 | | 3.24 | 3.55 | 3.41 | 3.59 | 3.43 |
|  |  |  |  | Values in percentage (%) | | | | | | |  |  |
| Black | 41.58 | 37.46 | 87.25 | 82.08 | 68.17 | | 61.09 | | 70.84 | 64.40 | 76.36 | 69.69 |
| High School | 48.55 | 48.81 | 53.44 | 58.89 | 50.70 | | 52.97 | | 51.84 | 55.39 | 53.43 | 59.39 |
| University | 21.66 | 31.49 | 13.04 | 24.05 | 14.48 | | 29.42 | | 9.26 | 22.43 | 14.95 | 26.99 |
| Formal job | 85.94 | 84.9 | 85.11 | 80.08 | 85.64 | | 80.06 | | 78.13 | 77.38 | 79.49 | 75.79 |
| Married | 3.74 | 3.91 | 3.49 | 3.85 | 3.69 | | 3.45 | | 4.83 | 5.12 | 4.54 | 4.59 |
| Manufacturing | 24.1 | 11.58 | 12.21 | 3.78 | 14.77 | | 6.43 | | 19.68 | 19.52 | 11.01 | 4.45 |
| Construction | 7.12 | 1.04 | 15.00 | 1.07 | 10.61 | | 1.04 | | 11.58 | 1.06 | 14.04 | 1.25 |
| Oth. Industries | 10.38 | 0.24 | 1.89 | 0.92 | 1.35 | | 0.64 | | 0.75 | 0.35 | 0.91 | 0.28 |
| Commerce | 20.95 | 17.12 | 21.94 | 19.62 | 22.86 | | 20.34 | | 28.34 | 18.46 | 26.46 | 25.03 |
| Services | 22.07 | 39.96 | 24.02 | 47.82 | 24.38 | | 46.62 | | 22.07 | 42.05 | 23.43 | 44.37 |
| Public Sector | 4.52 | 4.68 | 7.59 | 8.28 | 9.55 | | 8.92 | | 7.15 | 7.51 | 12.22 | 14.32 |
| Oth. Activities | 19.92 | 25.35 | 12.02 | 18.41 | 16.41 | | 15.99 | | 10.28 | 11.04 | 11.72 | 10.29 |
| Observations | 2,795,120 | 2,574,728 | 541,634 | 451,112 | 459,831 | | 335,519 | | 496,607 | 383,460 | 214,817 | 156,284 |

Source: Authors’ calculus using micro data from PNAD. “M” and “W” refer, respectively, to men and women. Wages are in logarithm of the average wage, measured in R$ of 2014; “Age” is measured in years; “Family size” is the average number of individuals per family; and ”Oth. Industries” includes extractive industries.

In the Figure 2, we present kernel density estimates for the distribution of the log. of real hourly wage for each of the metropolitan region, both for men and women[[4]](#footnote-4). By performing Kruskal-Wallis tests (Kruskal and Wallis 1952, 1953) for regional wage distributions, we reject the hypothesis that the samples come from the same population, so we consider them separately. For both men and women, the figure indicates that the density for São Paulo lies fairly to the right of those observed for the northern metropolitan regions, an evidence clearer form men than for women. Relative to northern metropolitan regions, the density for São Paulo also present a higher area of probability in the upper tail. Notice also that Recife and Salvador metropolitan regions present more similar distributions, evidence consistent with their similar sizes and characteristics.

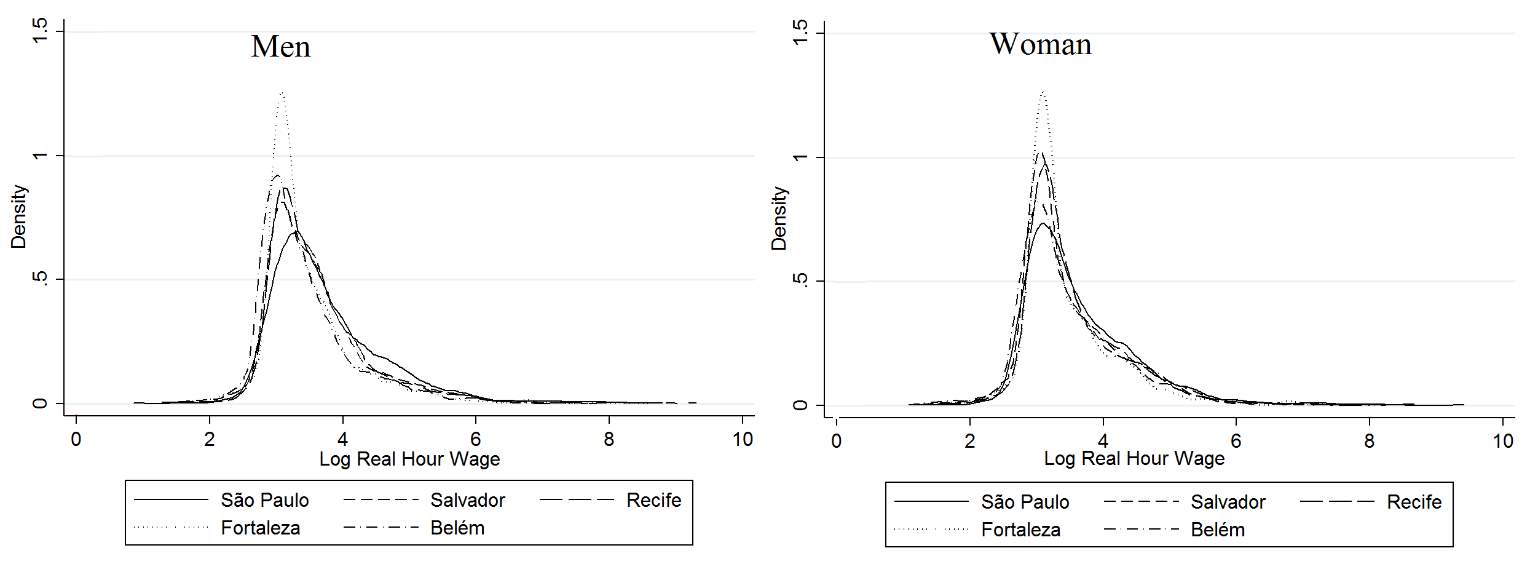


Figure 2. Log of real hourly wage kernel density estimates - Brazilian Metropolitan Regions.

**4. Results**

**4.1 Regional inequality across the wage distribution**

In the Table 3, we present the coefficients of the recentered influenced functions estimated for men at quantiles 0.1, 0.5, and 0.9 in each of five metropolitan regions[[5]](#footnote-5). We have performed Wald tests for the hypothesis of equality of coefficients between OLS and each of these quantiles estimative and between pair of quantiles estimative (specifically, 0.9–0.1, 0.9–0.5, 0.5–0.10, 0.7–0.3) and in all cases we confirmed that difference are statically significant at 5% significance level. In spite of being statistically different across quantiles and present variations across metropolitan regions, in general, the coefficients present expected signals.

Specifically, considering the traditional individual characteristics, we notice that higher schooling, more experience, non-black, and married individuals are circumstances that in general are associated with higher wages in all metropolitan regions. However, note that while the influence of high school degree tend to increase the higher the quantile for the northern regions, this does not happen to São Paulo. Furthermore, for the quantile 0.1 the returns for both high school and college degrees are much higher in this last metropolitan region than in all four northern regions, something that does not happen when considering higher quantiles (see the top graphics of Figure 3). This evidence indicates that the returns to schooling in the lower quantiles of income are favored by the larger labor market of São Paulo. Interestingly, we also observe that the negative differential associated with black individual increased with the quantiles of wage distributions, the highest difference occurring for the quantile 0.9 of Salvador metropolitan region. This suggests that race discrimination tend to be stronger for higher quantiles.

As for labor market characteristics, from Table 3, we observe that the wage differential of the sectors of activities relative to the Manufacture (the reference) is generally negative, except for the “other industries” category (that include both extractive and industrial service of public utility) and for “public sector” (that include all kind of government occupations). Reflecting the stronger importance of the government in their economies, we note that the positive differential favoring the public sector occupation is bigger the higher the quantiles of wage distribution in the northern metropolitan regions (see the bottom part of Figure 3). Actually, for the lower quantiles, this differential is always bigger for these regions than for São Paulo metropolitan regions. Finally, except for the case of Belém metropolitan region, notice that a formal job is more important the lower the quantile of the wage distribution.

**Table 3 – Coefficients estimate of Unconditional Quantile Regression for Men – Dependent variable is the log. of hourly wage.**

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Variables | São Paulo | | | Salvador | | | Recife | | | Fortaleza | | | Belém | | |
| Q10 | Q50 | Q90 | Q10 | Q50 | Q90 | Q10 | Q50 | Q90 | Q10 | Q50 | Q90 | Q10 | Q50 | Q90 |
| High School | 0.177\* | 0.299\* | 0.161\* | 0.086\* | 0.371\* | 0.374\* | 0.088\* | 0.244\* | 0.408\* | 0.068\* | 0.235\* | 0.259\* | 0.080\* | 0.236\* | 0.330\* |
|  | (0.001) | (0.001) | (0.003) | (0.001) | (0.002) | (0.006) | (0.002) | (0.002) | (0.005) | (0.001) | (0.002) | (0.004) | (0.002) | (0.003) | (0.009) |
| Universitty | 0.290\* | 0.874\* | 3.153\* | 0.134\* | 0.983\* | 3.455\* | 0.138\* | 0.655\* | 3.220\* | 0.087\* | 0.601\* | 2.741\* | 0.117\* | 0.605\* | 4.080\* |
|  | (0.001) | (0.001) | (0.006) | (0.001) | (0.003) | (0.015) | (0.002) | (0.002) | (0.013) | (0.001) | (0.002) | (0.012) | (0.002) | (0.003) | (0.027) |
| Construction | 0.015\* | -0.027\* | 0.420\* | -0.001 | -0.175\* | -0.451\* | 0.097\* | 0.015\* | -0.062\* | 0.022\* | 0.095\* | 0.197\* | 0.029\* | 0.123\* | 0.169\* |
|  | (0.001) | (0.002) | (0.007) | (0.002) | (0.004) | (0.011) | (0.002) | (0.004) | (0.009) | (0.001) | (0.003) | (0.007) | (0.003) | (0.004) | (0.015) |
| Others Industries | 0.069\* | 0.207\* | 0.641\* | 0.034\* | 0.170\* | 1.799\* | 0.036\* | 0.365\* | 0.175\* | -0.049\* | 0.240\* | 0.367\* | 0.066\* | 0.293\* | -0.359\* |
|  | (0.001) | (0.004) | (0.020) | (0.001) | (0.006) | (0.034) | (0.004) | (0.007) | (0.023) | (0.004) | (0.008) | (0.016) | (0.003) | (0.010) | (0.061) |
| Commerce | -0.135\* | -0.208\* | -0.179\* | -0.138\* | -0.304\* | -0.582\* | -0.058\* | -0.141\* | -0.284\* | -0.060\* | -0.063\* | -0.054\* | -0.055\* | -0.063\* | 0.077\* |
|  | (0.001) | (0.001) | (0.004) | (0.002) | (0.004) | (0.010) | (0.002) | (0.003) | (0.007) | (0.001) | (0.002) | (0.005) | (0.003) | (0.004) | (0.011) |
| Services | -0.081\* | -0.083\* | -0.337\* | -0.029\* | -0.139\* | -0.511\* | -0.018\* | 0.098\* | -0.201\* | 0.004\* | 0.068\* | 0.139\* | 0.051\* | 0.196\* | 0.485\* |
|  | (0.001) | (0.001) | (0.004) | (0.001) | (0.004) | (0.011) | (0.002) | (0.003) | (0.009) | (0.001) | (0.002) | (0.006) | (0.003) | (0.004) | (0.016) |
| Public Sector | -0.081\* | 0.164\* | 0.050\* | 0.046\* | 0.238\* | 0.512\* | 0.080\* | 0.343\* | 0.646\* | 0.047\* | 0.237\* | 1.146\* | 0.069\* | 0.362\* | 1.599\* |
|  | (0.001) | (0.002) | (0.010) | (0.001) | (0.004) | (0.018) | (0.002) | (0.003) | (0.015) | (0.001) | (0.003) | (0.012) | (0.003) | (0.004) | (0.026) |
| Other Activities | -0.014\* | -0.001 | 0.161\* | -0.002 | -0.217\* | -0.593\* | -0.014\* | -0.076\* | -0.165\* | 0.024\* | 0.021\* | -0.066\* | 0.066\* | 0.110\* | 0.293\* |
|  | (0.001) | (0.001) | (0.005) | (0.001) | (0.004) | (0.011) | (0.002) | (0.003) | (0.009) | (0.001) | (0.003) | (0.007) | (0.003) | (0.005) | (0.017) |
| Experience | 0.014\* | 0.031\* | 0.042\* | 0.006\* | 0.028\* | 0.043\* | 0.008\* | 0.013\* | 0.044\* | 0.004\* | 0.014\* | 0.026\* | 0.007\* | 0.013\* | 0.049\* |
|  | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) | (0.000) | (0.000) | (0.001) | (0.000) | (0.000) | (0.001) | (0.000) | (0.000) | (0.001) |
| Experience2 | -0.000\* | -0.000\* | -0.001\* | -0.000\* | -0.000\* | -0.000\* | -0.000\* | -0.000\* | -0.001\* | -0.000\* | -0.000\* | -0.000\* | -0.000\* | -0.000\* | -0.000\* |
|  | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Married | 0.040\* | 0.010\* | 0.153\* | -0.060\* | 0.010\* | 0.405\* | -0.022\* | 0.057\* | -0.217\* | 0.025\* | -0.119\* | -0.232\* | 0.069\* | 0.141\* | -0.148\* |
|  | (0.002) | (0.002) | (0.008) | (0.003) | (0.005) | (0.017) | (0.003) | (0.005) | (0.011) | (0.001) | (0.003) | (0.006) | (0.002) | (0.005) | (0.018) |
| Black | -0.023\* | -0.171\* | -0.428\* | -0.060\* | -0.141\* | -0.617\* | -0.031\* | -0.094\* | -0.310\* | -0.008\* | -0.012\* | -0.171\* | -0.007\* | -0.053\* | -0.059\* |
|  | (0.001) | (0.001) | (0.003) | (0.001) | (0.003) | (0.011) | (0.001) | (0.002) | (0.006) | (0.001) | (0.002) | (0.004) | (0.001) | (0.002) | (0.013) |
| Formal job | 0.257\* | 0.109\* | -0.108\* | 0.202\* | 0.262\* | 0.150\* | 0.175\* | 0.113\* | -0.176\* | 0.220\* | 0.045\* | 0.007 | 0.150\* | 0.069\* | 0.234\* |
|  | (0.001) | (0.001) | (0.004) | (0.002) | (0.003) | (0.007) | (0.002) | (0.002) | (0.008) | (0.001) | (0.002) | (0.004) | (0.002) | (0.003) | (0.013) |
| Family size | -0.017\* | -0.017\* | -0.012\* | -0.001\* | -0.002\* | 0.027\* | -0.005\* | -0.034\* | -0.021\* | 0.004\* | -0.020\* | -0.003\*\* | -0.012\* | -0.033\* | 0.029\* |
|  | (0.000) | (0.000) | (0.001) | (0.000) | (0.001) | (0.002) | (0.000) | (0.001) | (0.002) | (0.000) | (0.001) | (0.001) | (0.001) | (0.001) | (0.003) |
| Constant | 2.522\* | 2.940\* | 3.948\* | 2.698\* | 2.781\* | 4.038\* | 2.673\* | 3.105\* | 3.781\* | 2.680\* | 2.897\* | 3.602\* | 2.585\* | 2.817\* | 2.272\* |
|  | (0.002) | (0.002) | (0.008) | (0.003) | (0.006) | (0.016) | (0.004) | (0.005) | (0.012) | (0.002) | (0.004) | (0.010) | (0.004) | (0.006) | (0.026) |
| Observations | 2,795,120 | 2,795,120 | 2,795,120 | 541,634 | 541,634 | 541,634 | 459,831 | 459,831 | 459,831 | 496,607 | 496,607 | 496,607 | 214,817 | 214,817 | 214,817 |
| R2 | 0.104 | 0.270 | 0.217 | 0.134 | 0.250 | 0.296 | 0.077 | 0.214 | 0.316 | 0.152 | 0.154 | 0.329 | 0.137 | 0.275 | 0.331 |

Note: Robust Standard Errors at Parenthesis.\* means P-value < 0.01. For schooling variables, the reference is less than high school degree; and for sector of activities, the reference is the Manufacture sector.

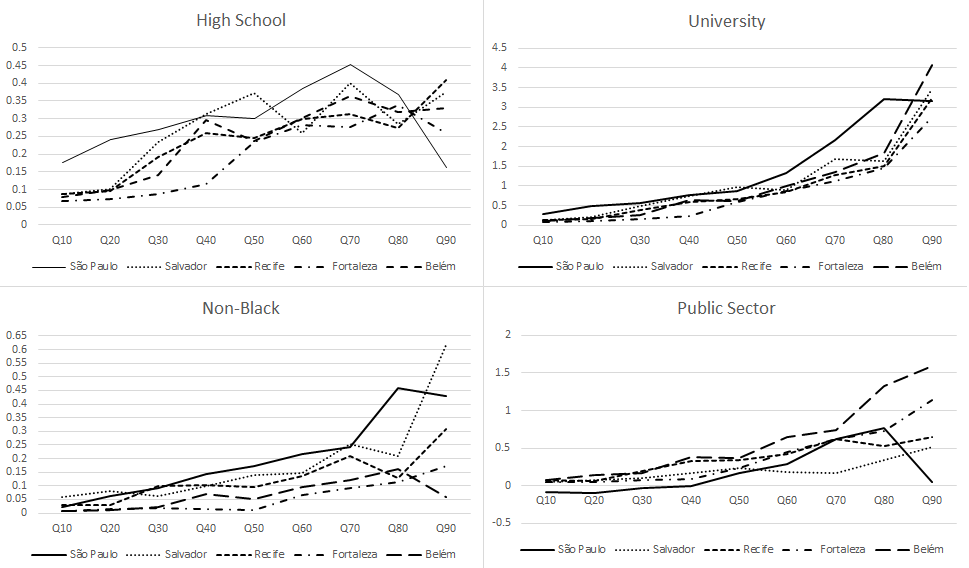


Figure 3 - Coefficients estimate of Unconditional Quantile Regression for Men. Selected categories.

This set of the estimates suggest that, in addition to regional differences in the composition of labor market (as shown in Table 1), the Brazilian regional differentials of returns to individual and labor market characteristics may play a relevant role in understanding the wages gaps between São Paulo and the Northern metropolitan regions across the wage distribution. These differentials are presented in the following Figure 4 (men) and Figure 5 (women) and Table 4, together with the average wage differentials (obtained through a traditional OLS regression) and their two components (composition and wage structure effects).

Two important evidences must be initially highlighted. First, we note that there is a clear pattern for Brazilian regional inequalities between São Paulo and Northern metropolitan regions: generally, the regional wage gap favorable to São Paulo metropolitan region increases, the higher the quantile of the wages distribution. More specifically, for example, both for men and women, we notice that for the quantile 0.1 the differentials are close to zero or even negative in the cases of Recife and Fortaleza metropolitan regions. On the other hand, the regional wage differentials are greater at the higher quantiles 0.8-0.9. Consequently, it is also possible to note that traditional average wage differentials (dot lines in the figures) are good approximation for the wage differential only for quantiles around the 0.5 quantile. Second, notice that the regional differentials can be substantial and vary not only across quantiles, but also across northern regions. The highest regional gaps are found for the case of Fortaleza (for quantile 0.8, where the wage in São Paulo is 63% higher for men) and the lowest regional gaps are present in the case of Salvador (where, for men, the highest differential, around 27%, is registered also for quantile 0.8).

Notice that this pattern of regional inequality is similar to that obtained by Perreira and Galego (2014), when comparing Lisbon to others Portuguese regions, but it is different from the set evidence obtained by Oliveira and Silveira Neto (2017) when comparing Southeast and Northeast Brazilian macro regions. The difference is, thus, consistent with the fact that we are considering only more developed and urbanized locations, which discard the poorest rural population of Northern states. Furthermore, the more significant regional wage gaps registered for higher quantiles of wage distributions suggest greater benefices for more skilled individuals living in the Brazilian great megalopolis. Still, the set of evidence we obtained here suggests that the regional wage gaps between São Paulo and the Northern metropolitan regions are hardly explained by some lack of regional mobility of workers across regions (that tends to be more serious for low-skilled individuals) and favors interpretations based on spatial equilibrium models (Gleaser and Maré, 2001; Gleaser, 2008).

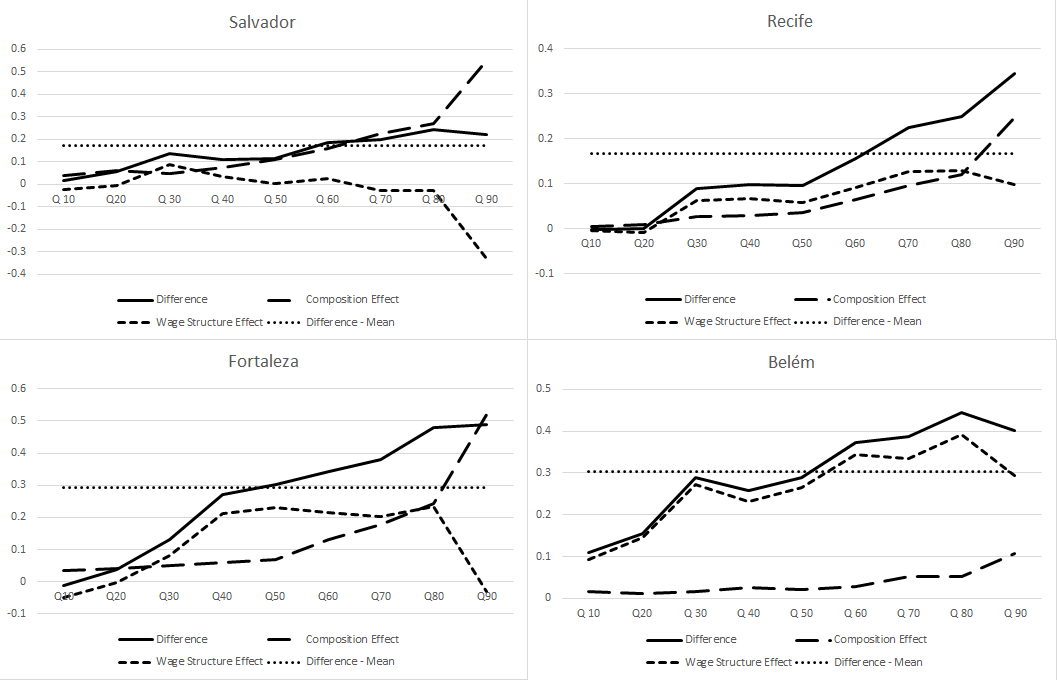


Figure 4 - Estimated regional wage differentials for men – São Paulo and Northern metropolitan regions.

The horizontal dotted line is the average estimated differential.

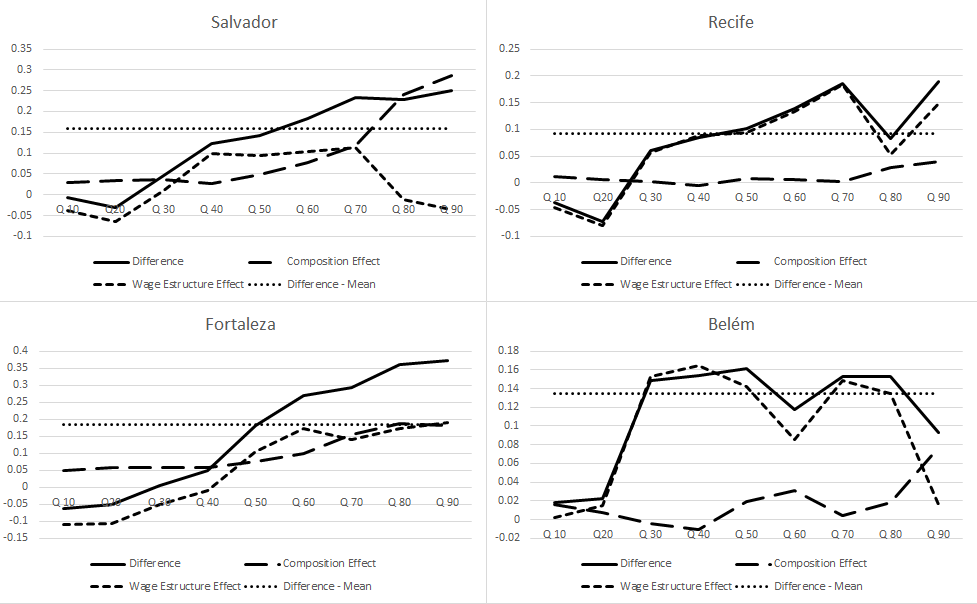


Figure 5 - Estimated regional wage differentials for women – São Paulo and Northern metropolitan regions.

The horizontal dotted line is the average estimated differential.

Figures 4 and 5 and Table 4 also present the contributions of the composition and wage structure effects to the registered regional gaps across the wage distributions. As for the wage gaps measured in the mean (OLS), we note that both components favor the metropolitan region of SP. But while the composition effect is more important for Salvador and Fortaleza (representing, respectively, 98.2% and 66.7% of the wage gaps), the wage structure effect is the main factor for Recife and Belém (preforming 53% and 83.9% of the wage gaps, respectively). Actually, except for a few number of quantiles for women wage gap distribution in Belém, the composition effects always contribute to increase wage gaps favoring SP. Thus, individual and labor markets characteristics clearly favor this metropolitan region. The importance of this effect and direction of the wage structure effects, however, vary substantially across quantiles and MRs.

First note that, except for the case of Belém, for the lowest quantiles (men and women), the above observed smaller regional gaps derive from positive composition effects and negative wage structure effects. Thus, while individual and labor markets characteristics favor SP, the returns favor northeast regions, a result similar to those obtained for men distribution by Galego and Pereira (2014) comparing Lisbon to other Portuguese regions. This is an interesting result and indicates that low-wage workers are favored in the northern regions. For the quantiles around the median, however, both effects generally contribute positively to the wage gaps. Finally, again excluding the case of Belém and focusing on the distributions for men, we note that the composition effect is responsible for the most of the wage gaps at the highest quantiles of the wage distribution, an important result since the biggest regional wage gaps are found exactly at these highest quantiles. This specific evidence differs from those obtained for men distribution by Galego and Pereira (2014). On the other hand, for the wage distributions of women, the wage structure effects generate most of the wage gaps at these highest quantiles in Recife and Fortaleza.

Table 4 – Decomposition of regional differential across wage distributions – São Paulo and the Brazilian Northern metropolitan regions

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Salvador | | Recife | | Fortaleza | | Belém | |
|  | Men | Women | Men | Women | Men | Women | Men | Women |
| OLS |  |  |  |  |  |  |  |  |
| Raw Difference | 0.171\*\*\* | 0.159\*\*\* | 0.168\*\*\* | 0.092\*\*\* | 0.294\*\*\* | 0.185\*\*\* | 0.304\*\*\* | 0.135\*\*\* |
|  | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) |
| Characteristics | 0.168\*\*\* | 0.106\*\*\* | 0.079\*\*\* | 0.013\*\*\* | 0.156\*\*\* | 0.122\*\*\* | 0.049\*\*\* | 0.030\*\*\* |
|  | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) |
| Coefficients | 0.003\*\* | 0.053\*\*\* | 0.090\*\*\* | 0.079\*\*\* | 0.138\*\*\* | 0.063\*\*\* | 0.255\*\*\* | 0.105\*\*\* |
|  | (0.002) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) | (0.003) |
| Quantile 0.10 |  |  |  |  |  |  |  |  |
| Raw Difference | 0.017\*\*\* | -0.008\*\*\* | -0.001 | -0.036\*\*\* | -0.012\*\*\* | -0.062\*\*\* | 0.109\*\*\* | 0.018\*\*\* |
|  | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Characteristics | 0.041\*\*\* | 0.030\*\*\* | 0.004\*\*\* | 0.011\*\*\* | 0.036\*\*\* | 0.048\*\*\* | 0.016\*\*\* | 0.016\*\*\* |
|  | (0.001) | (0.001) | (0.000) | (0.001) | (0.000) | (0.000) | (0.001) | (0.001) |
| Coefficients | -0.024\*\*\* | -0.038\*\*\* | -0.005\*\*\* | -0.047\*\*\* | -0.048\*\*\* | -0.110\*\*\* | 0.093\*\*\* | 0.002\* |
|  | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Quantile 0.30 |  |  |  |  |  |  |  |  |
| Raw Difference | 0.135\*\*\* | 0.046\*\*\* | 0.089\*\*\* | 0.060\*\*\* | 0.131\*\*\* | 0.005\*\*\* | 0.290\*\*\* | 0.149\*\*\* |
|  | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Characteristics | 0.049\*\*\* | 0.036\*\*\* | 0.027\*\*\* | 0.003\*\*\* | 0.051\*\*\* | 0.057\*\*\* | 0.017\*\*\* | -0.004\*\*\* |
|  | (0.001) | (0.001) | (0.001) | (0.001) | (0.000) | (0.001) | (0.001) | (0.001) |
| Coefficients | 0.086\*\*\* | 0.010\*\*\* | 0.062\*\*\* | 0.056\*\*\* | 0.080\*\*\* | -0.052\*\*\* | 0.273\*\*\* | 0.153\*\*\* |
|  | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) |
| Quantile 0.50 |  |  |  |  |  |  |  |  |
| Raw Difference | 0.114\*\*\* | 0.143\*\*\* | 0.095\*\*\* | 0.101\*\*\* | 0.302\*\*\* | 0.181\*\*\* | 0.288\*\*\* | 0.161\*\*\* |
|  | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) |
| Characteristics | 0.109\*\*\* | 0.048\*\*\* | 0.036\*\*\* | 0.008\*\*\* | 0.070\*\*\* | 0.076\*\*\* | 0.022\*\*\* | 0.019\*\*\* |
|  | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) |
| Coefficients | 0.005\*\*\* | 0.095\*\*\* | 0.059\*\*\* | 0.094\*\*\* | 0.231\*\*\* | 0.105\*\*\* | 0.265\*\*\* | 0.142\*\*\* |
|  | (0.002) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) |
| Quantile 0.70 |  |  |  |  |  |  |  |  |
| Raw Difference | 0.200\*\*\* | 0.233\*\*\* | 0.224\*\*\* | 0.186\*\*\* | 0.381\*\*\* | 0.293\*\*\* | 0.387\*\*\* | 0.153\*\*\* |
|  | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.003) |
| Characteristics | 0.228\*\*\* | 0.119\*\*\* | 0.096\*\*\* | 0.003 | 0.178\*\*\* | 0.154\*\*\* | 0.052\*\*\* | 0.004 |
|  | (0.002) | (0.002) | (0.001) | (0.002) | (0.001) | (0.002) | (0.002) | (0.004) |
| Coefficients | -0.028\*\*\* | 0.114\*\*\* | 0.128\*\*\* | 0.183\*\*\* | 0.203\*\*\* | 0.139\*\*\* | 0.335\*\*\* | 0.149\*\*\* |
|  | (0.002) | (0.003) | (0.002) | (0.002) | (0.002) | (0.002) | (0.003) | (0.004) |
| Quantile 0.90 |  |  |  |  |  |  |  |  |
| Raw Difference | 0.223\*\*\* | 0.251\*\*\* | 0.345\*\*\* | 0.189\*\*\* | 0.490\*\*\* | 0.372\*\*\* | 0.402\*\*\* | 0.093\*\*\* |
|  | (0.004) | (0.003) | (0.004) | (0.004) | (0.004) | (0.003) | (0.006) | (0.005) |
| Characteristics | 0.552\*\*\* | 0.287\*\*\* | 0.247\*\*\* | 0.039\*\*\* | 0.520\*\*\* | 0.182\*\*\* | 0.108\*\*\* | 0.077\*\*\* |
|  | (0.006) | (0.004) | (0.003) | (0.002) | (0.004) | (0.003) | (0.006) | (0.006) |
| Coefficients | -0.329\*\*\* | -0.036\*\*\* | 0.099\*\*\* | 0.149\*\*\* | -0.030\*\*\* | 0.190\*\*\* | 0.294\*\*\* | 0.016\*\* |
|  | (0.007) | (0.006) | (0.004) | (0.004) | (0.005) | (0.004) | (0.007) | (0.007) |

Note: Aggregate decomposition using recentered influence functions. Robust Standard Errors at Parenthesis. \*\*\*

means p-value < 0.01.

**4.2 Detailed decompositions: factors associated with regional differentials across the wage distribution**

In the following Tables 5-9, we present the results of the detailed decomposition for the wage gaps between SP and each of the northern metropolitan regions, respectively, for the OLS traditional estimation (mean), and quantiles 0.1, 0.5, and 0.9 (both for men and women)[[6]](#footnote-6). There are three common important patterns to highlight. First, in most of the cases for the composition effect, a university degree and being a black worker are the most important variables favoring the SP metropolitan region and generally can explain entirely this effect. Second, similarly to the results obtained by Oliveira and Silveira Neto (2017) comparing Brazilian Southeast and Northeast regions in 2010, there is no situation that the economic activities structure (“sectors”) do play a relevant role for understanding the composition effect favoring SP. Third, in almost all the cases, the returns to experience importantly contribute to the wage structure effect.

There are also, however, substantial differences across quantiles and metropolitan regions. Notice that while a university degree is generally the most important characteristic for explaining the composition effect favoring SP for the mean and median and higher quantiles, for quantile 0.1 the variable associated with the race of the worker (black) and formal occupation conditions also play protagonist roles. Similar evidence about schooling contribution was also obtained by Galego and Pereira (2014) and Oliveira and Silveira Neto (2017). For quantile 0.1 in Salvador, for example, factors associated with being a black worker is responsible for 87.8% and 63.3% of the composition effects for men and women, respectively. As for the same quantile in Fortaleza, the condition of having a formal job is associated with 55.6% and 43.7% of the composition effects for men and women, respectively. But the higher the quantile, the less relevant tend to be a formal job for the composition effects favoring SP and the university degree and black conditions assume almost total protagonist roles. Actually, for the men’s distributions, for example, except for the case of Salvador (where factors associated with race are also always relevant), factors associated with a university degree are responsible for practically all of the composition effects both in quantiles 0.5 and 0.9. Remembering the numbers of Table 4, this means that these factors can explain almost all the wage gaps between SP and Recife and Fortaleza in the highest quantile.

As for the wage structure effect, in general, the main factor associated with it is the returns to experience, a result also similar to that generated by Galego and Pereira (2014), although the returns to schooling variables also matter for intermediary and higher quantiles (where regional gaps are significant). This result is consistent with greater learning and better matching in urban bigger labor markets (Glaeser and Maré, 2001; Galego and Pereira, 2014). The results of Table 5 for the traditional Oaxaca-Blinder decomposition (at the mean) indicate, for example, that, both for men and women, the higher contributions are found for Recife, where around 87.7% and 100% of the effect arise from the factors associated with the returns to experience, respectively. This relevance is even clearer for quantiles 0.5 and 0.9, but with an important difference: for men in quantile 0.9 the returns to experience favor northern metropolitan regions and not SP. In other words, while for intermediary level of wages the returns to experience in SP bigger labor market favor both men and women, for high-wage occupations these greater gains relative to northern metropolitan regions favor only women. This evidence suggests that agglomeration gains in high-wage positions associated with the permanence in a bigger labor markets in Brazil matter more for women than for men and it is consistent with the fact that even non-married women may have harder conditions of spatial arbitrage and, thus, derive more advantage of a bigger labor market (Silveira Neto et al. 2016; Kawabata and Abe, 2018).

Taking all together, the set of evidence obtained in this research suggest different situations and reasons behind the regional wage disparities between SP and Brazilian northern regions. For the highest quantiles of the wage distributions (where regional inequality is bigger) and for men and excluding the case of Belém, the set of factors associated with it (individual characteristics acting through the composition effect, mainly a university degree) suggests that the wage gaps area entirely consistent with spatial equilibrium models (Gleaser and Maré, 2001; Gleaser 2011). For these higher quantiles, the same is true for women in Salvador, but not for the other three regions. Here, the wages gaps are also consistent with greater agglomeration gains in SP and lack of mobility that in general characterize women in Brazilian labor markets. On the other hand, for lowest quantiles, where the lack of mobility tends to be greater but no significant wage gaps were found, the situation suggests that the potential greater agglomeration gains in SP do not clearly beneficiate these workers.

As for the intermediary quantiles, where, except for men in Salvador, the structure wage effect tends to be more important, the results are more similar for men and women and may support different explanations for the regional wage gaps. The relevance of the structure wage effect is consistent with is the potential greater agglomeration gains in SP and possible lack of spatial mobility for workers of these quantiles. The fact that the effect is stronger for women than men appear strengthens the possibility. On the other hand, at least for Recife and Fortaleza, the situation is also consistent with their more favorable stock of natural amenities (Silveira Neto and Menezes, 2008).

Finally, as the above characterization makes clear, the regional inequality between SP and Belém metropolitan regions presents the particular characteristic that, with few exceptions, income gaps across the wage distribution are almost entirely associated with the wage structure effect, being workers characteristics much less important. Given the great difference in the magnitudes between these regions, as they represent the biggest (SP) and smallest (Belém) labor markets in analysis, this result is consistent with more substantial benefits of urban agglomeration gains in the first region and is in line with the results of Baruffi et al. (2017).

Table 5 – Detailed Decomposition of regional differential at mean – São Paulo and the Brazilian Northern metropolitan regions – Mean.

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Men | | | | Women | | | | |
|  | Salvador | Recife | Fortaleza | Belém | | Salvador | Recife | Fortaleza | Belém |
| *Comp. Effect* | 0.168\*\*\* | 0.079\*\*\* | 0.156\*\*\* | 0.049\*\*\* | | 0.106\*\*\* | 0.013\*\*\* | 0.122\*\*\* | 0.030\*\*\* |
|  | (0.001) | (0.001) | (0.001) | (0.002) | | (0.001) | (0.001) | (0.001) | (0.002) |
| High School | -0.013\*\*\* | -0.006\*\*\* | -0.009\*\*\* | -0.011\*\*\* | | -0.023\*\*\* | -0.008\*\*\* | -0.012\*\*\* | -0.031\*\*\* |
|  | (0.000) | (0.000) | (0.000) | (0.000) | | (0.000) | (0.000) | (0.000) | (0.001) |
| University | 0.105\*\*\* | 0.085\*\*\* | 0.144\*\*\* | 0.080\*\*\* | | 0.081\*\*\* | 0.021\*\*\* | 0.085\*\*\* | 0.054\*\*\* |
|  | (0.001) | (0.001) | (0.001) | (0.001) | | (0.001) | (0.001) | (0.001) | (0.001) |
| Sectors | 0.001\* | -0.022\*\*\* | -0.012\*\*\* | -0.044\*\*\* | | -0.023\*\*\* | -0.022\*\*\* | 0.012\*\*\* | -0.022\*\*\* |
|  | (0.000) | (0.000) | (0.000) | (0.001) | | (0.000) | (0.000) | (0.001) | (0.001) |
| Experience | -0.020\*\*\* | -0.020\*\*\* | -0.001\*\*\* | -0.017\*\*\* | | -0.006\*\*\* | -0.004\*\*\* | 0.003\*\*\* | -0.019\*\*\* |
|  | (0.000) | (0.000) | (0.000) | (0.000) | | (0.000) | (0.000) | (0.000) | (0.000) |
| Black | 0.093\*\*\* | 0.043\*\*\* | 0.024\*\*\* | 0.030\*\*\* | | 0.070\*\*\* | 0.015\*\*\* | 0.017\*\*\* | 0.021\*\*\* |
|  | (0.001) | (0.001) | (0.001) | (0.001) | | (0.001) | (0.000) | (0.001) | (0.001) |
| Formal | 0.002\*\*\* | 0.000\*\*\* | 0.008\*\*\* | 0.009\*\*\* | | 0.010\*\*\* | 0.010\*\*\* | 0.013\*\*\* | 0.025\*\*\* |
|  | (0.000) | (0.000) | (0.000) | (0.000) | | (0.000) | (0.000) | (0.000) | (0.000) |
| Others | -0.000 | -0.001\*\*\* | 0.001\*\*\* | 0.001\*\*\* | | -0.003\*\*\* | 0.000\*\*\* | 0.003\*\*\* | 0.002\*\*\* |
|  | (0.000) | (0.000) | (0.000) | (0.000) | | (0.000) | (0.000) | (0.000) | (0.000) |
| *W.S. Effect* | 0.003\*\* | 0.090\*\*\* | 0.138\*\*\* | 0.255\*\*\* | | 0.053\*\*\* | 0.079\*\*\* | 0.063\*\*\* | 0.105\*\*\* |
|  | (0.002) | (0.001) | (0.001) | (0.002) | | (0.001) | (0.001) | (0.001) | (0.003) |
| High School | -0.001 | -0.015\*\*\* | -0.010\*\*\* | 0.012\*\*\* | | 0.013\*\*\* | 0.038\*\*\* | 0.040\*\*\* | -0.017\*\*\* |
|  | (0.001) | (0.001) | (0.001) | (0.001) | | (0.001) | (0.001) | (0.001) | (0.003) |
| University | -0.004\*\*\* | 0.005\*\*\* | 0.008\*\*\* | 0.001 | | 0.003\*\*\* | 0.025\*\*\* | 0.055\*\*\* | -0.027\*\*\* |
|  | (0.001) | (0.001) | (0.001) | (0.001) | | (0.001) | (0.001) | (0.001) | (0.002) |
| Sectors | 0.061\*\*\* | 0.022\*\*\* | 0.013\*\*\* | -0.002 | | 0.012\*\*\* | 0.071\*\*\* | -0.032\*\*\* | -0.078\*\*\* |
|  | (0.001) | (0.001) | (0.001) | (0.002) | | (0.002) | (0.003) | (0.004) | (0.002) |
| Experience | 0.029\*\*\* | 0.079\*\*\* | 0.084\*\*\* | 0.073\*\*\* | | 0.069\*\*\* | 0.141\*\*\* | 0.064\*\*\* | 0.066\*\*\* |
|  | (0.002) | (0.002) | (0.002) | (0.003) | | (0.002) | (0.003) | (0.002) | (0.004) |
| Black | 0.016\*\*\* | -0.001 | -0.034\*\*\* | -0.032\*\*\* | | 0.007\*\*\* | -0.027\*\*\* | -0.028\*\*\* | -0.027\*\*\* |
|  | (0.001) | (0.001) | (0.001) | (0.001) | | (0.001) | (0.001) | (0.001) | (0.001) |
| Formal | -0.140\*\*\* | -0.014\*\*\* | 0.010\*\*\* | -0.026\*\*\* | | -0.102\*\*\* | -0.095\*\*\* | -0.065\*\*\* | -0.150\*\*\* |
|  | (0.002) | (0.002) | (0.002) | (0.003) | | (0.002) | (0.002) | (0.002) | (0.004) |
| Others | -0.054\*\*\* | 0.017\*\*\* | -0.060\*\*\* | -0.005 | | -0.122\*\*\* | -0.181\*\*\* | -0.110\*\*\* | -0.088\*\*\* |
|  | (0.002) | (0.002) | (0.003) | (0.003) | | (0.003) | (0.003) | (0.002) | (0.004) |
| Constant | 0.095\*\*\* | -0.003 | 0.126\*\*\* | 0.235\*\*\* | | 0.173\*\*\* | 0.107\*\*\* | 0.139\*\*\* | 0.425\*\*\* |
|  | (0.005) | (0.005) | (0.005) | (0.007) | | (0.005) | (0.006) | (0.006) | (0.008) |

Note: Detailed decomposition using recentered influence functions. Robust Standard Errors at Parenthesis. \*\*\* and \*\* indicate, respectively, p-value<0.01 and p-value < 0.05. “Sectors” represents the effects of economic activities variables and “Others” includes the effects of family size and married.

Table 6 – Detailed Decomposition of regional differential – São Paulo and the Brazilian Northern metropolitan regions - Quantile 0.1.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Men | | | | Women | | | |
|  | Salvador | Recife | Fortaleza | Belém | Salvador | Recife | Fortaleza | Belém |
| *Comp. Effect* | 0.041\*\*\* | 0.004\*\*\* | 0.036\*\*\* | 0.016\*\*\* | 0.030\*\*\* | -0.047\*\*\* | 0.048\*\*\* | 0.016\*\*\* |
|  | (0.001) | (0.000) | (0.000) | (0.001) | (0.001) | -0.009\*\*\* | (0.000) | (0.001) |
| High School | -0.006\*\*\* | -0.002\*\*\* | -0.002\*\*\* | -0.005\*\*\* | -0.015\*\*\* | -0.009\*\*\* | -0.004\*\*\* | -0.027\*\*\* |
|  | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) |
| University | 0.015\*\*\* | 0.011\*\*\* | 0.012\*\*\* | 0.011\*\*\* | 0.015\*\*\* | 0.007\*\*\* | 0.011\*\*\* | 0.014\*\*\* |
|  | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Sectors | 0.000 | -0.008\*\*\* | 0.005\*\*\* | 0.001 | 0.002\*\*\* | -0.002\*\*\* | 0.009\*\*\* | -0.006\*\*\* |
|  | (0.000) | (0.000) | (0.000) | (0.001) | (0.000) | (0.000) | (0.000) | (0.001) |
| Experience | -0.006\*\*\* | -0.008\*\*\* | -0.000\*\*\* | -0.009\*\*\* | -0.004\*\*\* | -0.001\*\*\* | 0.001\*\*\* | -0.001\*\*\* |
|  | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Black | 0.036\*\*\* | 0.010\*\*\* | 0.003\*\*\* | 0.003\*\*\* | 0.019\*\*\* | 0.003\*\*\* | 0.008\*\*\* | 0.014\*\*\* |
|  | (0.001) | (0.000) | (0.000) | (0.001) | (0.000) | (0.000) | (0.000) | (0.001) |
| Formal | 0.002\*\*\* | 0.001\*\*\* | 0.020\*\*\* | 0.013\*\*\* | 0.016\*\*\* | 0.012\*\*\* | 0.021\*\*\* | 0.022\*\*\* |
|  | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Others | -0.000\*\*\* | -0.000\*\*\* | -0.001\*\*\* | 0.002\*\*\* | -0.004\*\*\* | 0.000\*\* | 0.002\*\*\* | -0.000\*\*\* |
|  | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| *W.S. Effect* | -0.024\*\*\* | -0.005\*\*\* | -0.048\*\*\* | 0.093\*\*\* | -0.038\*\*\* | -0.047\*\*\* | -0.110\*\*\* | 0.002\* |
|  | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| High School | 0.039\*\*\* | 0.045\*\*\* | 0.056\*\*\* | 0.041\*\*\* | 0.046\*\*\* | 0.006\*\*\* | 0.091\*\*\* | -0.006\*\*\* |
|  | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) | (0.001) | (0.002) |
| University | 0.031\*\*\* | 0.034\*\*\* | 0.047\*\*\* | 0.034\*\*\* | 0.040\*\*\* | 0.000 | 0.064\*\*\* | 0.002 |
|  | (0.000) | (0.000) | (0.000) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Sectors | 0.007\*\*\* | 0.009\*\*\* | -0.018\*\*\* | -0.002\*\*\* | -0.000 | -0.019\*\*\* | 0.017\*\*\* | 0.008\*\*\* |
|  | (0.000) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Experience | 0.080\*\*\* | 0.081\*\*\* | 0.122\*\*\* | 0.062\*\*\* | -0.004\*\* | 0.070\*\*\* | 0.031\*\*\* | 0.065\*\*\* |
|  | (0.002) | (0.002) | (0.002) | (0.003) | (0.002) | (0.002) | (0.002) | (0.003) |
| Black | 0.022\*\*\* | 0.004\*\*\* | -0.007\*\*\* | -0.007\*\*\* | 0.009\*\*\* | -0.002\*\*\* | 0.004\*\*\* | 0.009\*\*\* |
|  | (0.001) | (0.001) | (0.000) | (0.001) | (0.000) | (0.001) | (0.000) | (0.001) |
| Formal | 0.014\*\*\* | 0.069\*\*\* | 0.026\*\*\* | 0.066\*\*\* | -0.103\*\*\* | -0.037\*\*\* | -0.054\*\*\* | -0.028\*\*\* |
|  | (0.002) | (0.002) | (0.002) | (0.003) | (0.002) | (0.002) | (0.002) | (0.003) |
| Others | -0.055\*\*\* | -0.043\*\*\* | -0.078\*\*\* | -0.011\*\*\* | 0.026\*\*\* | -0.029\*\*\* | 0.022\*\*\* | -0.026\*\*\* |
|  | (0.002) | (0.002) | (0.002) | (0.003) | (0.002) | (0.002) | (0.002) | (0.003) |
| Constant | -0.163\*\*\* | -0.205\*\*\* | -0.196\*\*\* | -0.091\*\*\* | -0.050\*\*\* | -0.036\*\*\* | -0.284\*\*\* | -0.020\*\*\* |
|  | (0.004) | (0.005) | (0.004) | (0.006) | (0.004) | (0.005) | (0.004) | (0.006) |

Note: Detailed decomposition using recentered influence functions. Robust Standard Errors at Parenthesis. \*\*\* and \*\* indicate, respectively, p-value<0.01 and p-value < 0.05.

Table 7 – Detailed Decomposition of regional differential – São Paulo and the Brazilian Northern metropolitan regions - Quantile 0.5.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Men | | | | Women | | | |
|  | Salvador | Recife | Fortaleza | Belém | Salvador | Recife | Fortaleza | Belém |
| *Comp. Effect* | 0.109\*\*\* | 0.036\*\*\* | 0.070\*\*\* | 0.022\*\*\* | 0.048\*\*\* | 0.094\*\*\* | 0.076\*\*\* | 0.019\*\*\* |
|  | (0.001) | (0.001) | (0.001) | (0.002) | (0.001) | -0.008\*\*\* | (0.001) | (0.002) |
| High School | -0.017\*\*\* | -0.006\*\*\* | -0.007\*\*\* | -0.014\*\*\* | -0.030\*\*\* | -0.008\*\*\* | -0.013\*\*\* | -0.037\*\*\* |
|  | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) |
| University | 0.080\*\*\* | 0.052\*\*\* | 0.070\*\*\* | 0.049\*\*\* | 0.067\*\*\* | 0.017\*\*\* | 0.051\*\*\* | 0.045\*\*\* |
|  | (0.001) | (0.000) | (0.000) | (0.001) | (0.001) | (0.001) | (0.000) | (0.001) |
| Sectors | 0.004\*\*\* | -0.023\*\*\* | -0.003\*\*\* | -0.032\*\*\* | -0.021\*\*\* | -0.003\*\*\* | 0.024\*\*\* | -0.016\*\*\* |
|  | (0.000) | (0.000) | (0.000) | (0.001) | (0.000) | (0.000) | (0.000) | (0.001) |
| Experience | -0.020\*\*\* | -0.013\*\*\* | -0.001\*\*\* | -0.015\*\*\* | -0.002\*\*\* | -0.004\*\*\* | 0.002\*\*\* | -0.015\*\*\* |
|  | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Black | 0.061\*\*\* | 0.028\*\*\* | 0.003\*\*\* | 0.022\*\*\* | 0.032\*\*\* | 0.007\*\*\* | 0.004\*\*\* | 0.013\*\*\* |
|  | (0.001) | (0.001) | (0.000) | (0.001) | (0.001) | (0.000) | (0.000) | (0.001) |
| Formal | 0.002\*\*\* | 0.000\*\*\* | 0.003\*\*\* | 0.005\*\*\* | 0.006\*\*\* | -0.000\*\* | 0.005\*\*\* | 0.024\*\*\* |
|  | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Others | -0.000\*\*\* | -0.002\*\*\* | 0.004\*\*\* | 0.006\*\*\* | -0.004\*\*\* | -0.001\*\*\* | 0.002\*\*\* | 0.004\*\*\* |
|  | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| *W.S. Effect* | 0.005\*\*\* | 0.059\*\*\* | 0.231\*\*\* | 0.265\*\*\* | 0.095\*\*\* | 0.094\*\*\* | 0.105\*\*\* | 0.142\*\*\* |
|  | (0.002) | (0.001) | (0.001) | (0.002) | (0.001) | (0.001) | (0.001) | (0.002) |
| High School | -0.013\*\*\* | 0.026\*\*\* | 0.050\*\*\* | 0.018\*\*\* | 0.022\*\*\* | 0.078\*\*\* | 0.077\*\*\* | 0.001 |
|  | (0.001) | (0.001) | (0.001) | (0.002) | (0.001) | (0.002) | (0.001) | (0.002) |
| University | 0.004\*\*\* | 0.047\*\*\* | 0.082\*\*\* | 0.046\*\*\* | 0.083\*\*\* | 0.108\*\*\* | 0.187\*\*\* | 0.048\*\*\* |
|  | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) |
| Sectors | 0.005\*\*\* | 0.032\*\*\* | -0.011\*\*\* | 0.012\*\*\* | -0.055\*\*\* | -0.006\*\* | -0.071\*\*\* | -0.005 |
|  | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) | (0.003) | (0.003) | (0.004) |
| Experience | 0.059\*\*\* | 0.202\*\*\* | 0.210\*\*\* | 0.147\*\*\* | 0.088\*\*\* | 0.070\*\*\* | 0.099\*\*\* | 0.035\*\*\* |
|  | (0.003) | (0.003) | (0.002) | (0.004) | (0.002) | (0.003) | (0.002) | (0.004) |
| Black | -0.022\*\*\* | -0.033\*\*\* | -0.072\*\*\* | -0.050\*\*\* | -0.013\*\*\* | -0.030\*\*\* | -0.034\*\*\* | -0.025\*\*\* |
|  | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Formal | -0.111\*\*\* | -0.007\*\*\* | 0.064\*\*\* | 0.029\*\*\* | -0.085\*\*\* | 0.029\*\*\* | -0.035\*\*\* | -0.201\*\*\* |
|  | (0.002) | (0.003) | (0.002) | (0.003) | (0.002) | (0.002) | (0.002) | (0.003) |
| Others | -0.057\*\*\* | 0.063\*\*\* | 0.005\*\* | 0.065\*\*\* | -0.153\*\*\* | -0.163\*\*\* | -0.188\*\*\* | -0.075\*\*\* |
|  | (0.003) | (0.003) | (0.002) | (0.003) | (0.003) | (0.003) | (0.002) | (0.004) |
| Constant | 0.140\*\*\* | -0.270\*\*\* | -0.095\*\*\* | -0.002 | 0.208\*\*\* | 0.008 | 0.069\*\*\* | 0.365\*\*\* |
|  | (0.005) | (0.005) | (0.004) | (0.007) | (0.005) | (0.006) | (0.005) | (0.009) |

Note: Detailed decomposition using recentered influence functions. Robust standard errors at Parenthesis. \*\*\* and \*\* indicate, respectively, p-value<0.01 and p-value < 0.05.

Table 8 – Detailed Decomposition of regional differential – São Paulo and the Brazilian Northern metropolitan regions - Quantile 0.9.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Men | | | | Women | | | |
|  | Salvador | Recife | Fortaleza | Belém | Salvador | Recife | Fortaleza | Belém |
| *Comp. Effect* | 0.552\*\*\* | 0.247\*\*\* | 0.520\*\*\* | 0.108\*\*\* | 0.287\*\*\* | 0.149\*\*\* | 0.182\*\*\* | 0.077\*\*\* |
|  | (0.006) | (0.003) | (0.004) | (0.006) | (0.004) | -0.007\*\*\* | (0.003) | (0.006) |
| High School | -0.019\*\*\* | -0.009\*\*\* | -0.012\*\*\* | -0.014\*\*\* | -0.024\*\*\* | -0.007\*\*\* | -0.009\*\*\* | -0.005\*\*\* |
|  | (0.000) | (0.000) | (0.000) | (0.001) | (0.001) | (0.000) | (0.000) | (0.001) |
| University | 0.306\*\*\* | 0.244\*\*\* | 0.514\*\*\* | 0.245\*\*\* | 0.149\*\*\* | 0.033\*\*\* | 0.150\*\*\* | 0.079\*\*\* |
|  | (0.002) | (0.002) | (0.003) | (0.003) | (0.002) | (0.001) | (0.002) | (0.002) |
| Sectors | 0.003\*\* | -0.028\*\*\* | -0.061\*\*\* | -0.109\*\*\* | -0.043\*\*\* | -0.059\*\*\* | -0.021\*\*\* | -0.052\*\*\* |
|  | (0.002) | (0.001) | (0.001) | (0.003) | (0.001) | (0.001) | (0.001) | (0.003) |
| Experience | -0.038\*\*\* | -0.044\*\*\* | -0.003\*\*\* | -0.042\*\*\* | -0.008\*\*\* | -0.014\*\*\* | 0.005\*\*\* | -0.021\*\*\* |
|  | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.000) | (0.000) | (0.001) |
| Black | 0.291\*\*\* | 0.086\*\*\* | 0.076\*\*\* | 0.018\*\*\* | 0.200\*\*\* | 0.071\*\*\* | 0.035\*\*\* | 0.052\*\*\* |
|  | (0.005) | (0.002) | (0.002) | (0.004) | (0.004) | (0.001) | (0.002) | (0.003) |
| Formal | 0.001\*\*\* | -0.001\*\*\* | 0.001 | 0.013\*\*\* | 0.006\*\*\* | 0.009\*\*\* | 0.020\*\*\* | 0.024\*\*\* |
|  | (0.000) | (0.000) | (0.001) | (0.001) | (0.000) | (0.000) | (0.000) | (0.001) |
| Others | 0.007\*\*\* | -0.001\*\*\* | 0.005\*\*\* | -0.003\*\*\* | 0.007\*\*\* | 0.006\*\*\* | 0.002\*\*\* | 0.001\*\*\* |
|  | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) | (0.000) | (0.000) | (0.000) |
| *W.S. Effect* | -0.329\*\*\* | 0.099\*\*\* | -0.030\*\*\* | 0.294\*\*\* | -0.036\*\*\* | 0.149\*\*\* | 0.190\*\*\* | 0.016\*\* |
|  | (0.007) | (0.004) | (0.005) | (0.007) | (0.006) | (0.004) | (0.004) | (0.007) |
| High School | -0.132\*\*\* | -0.153\*\*\* | -0.134\*\*\* | -0.088\*\*\* | -0.034\*\*\* | 0.007\*\* | 0.016\*\*\* | 0.059\*\*\* |
|  | (0.003) | (0.003) | (0.003) | (0.004) | (0.003) | (0.003) | (0.003) | (0.006) |
| University | -0.282\*\*\* | -0.244\*\*\* | -0.409\*\*\* | -0.302\*\*\* | -0.054\*\*\* | 0.071\*\*\* | 0.056\*\*\* | 0.028\*\*\* |
|  | (0.004) | (0.003) | (0.004) | (0.005) | (0.004) | (0.003) | (0.003) | (0.006) |
| Sectors | 0.274\*\*\* | 0.026\*\*\* | 0.152\*\*\* | -0.053\*\*\* | -0.022\*\* | 0.051\*\*\* | -0.296\*\*\* | -0.158\*\*\* |
|  | (0.005) | (0.004) | (0.004) | (0.008) | (0.010) | (0.011) | (0.008) | (0.015) |
| Experience | -0.234\*\*\* | -0.219\*\*\* | -0.241\*\*\* | -0.302\*\*\* | 0.227\*\*\* | 0.232\*\*\* | 0.211\*\*\* | 0.401\*\*\* |
|  | (0.007) | (0.007) | (0.008) | (0.012) | (0.006) | (0.007) | (0.006) | (0.010) |
| Black | 0.137\*\*\* | 0.008\*\*\* | -0.020\*\*\* | -0.106\*\*\* | 0.068\*\*\* | 0.013\*\*\* | -0.051\*\*\* | -0.040\*\*\* |
|  | (0.005) | (0.003) | (0.003) | (0.005) | (0.003) | (0.002) | (0.002) | (0.004) |
| Formal | -0.200\*\*\* | 0.092\*\*\* | -0.076\*\*\* | -0.247\*\*\* | -0.136\*\*\* | -0.201\*\*\* | -0.257\*\*\* | -0.259\*\*\* |
|  | (0.006) | (0.008) | (0.006) | (0.010) | (0.006) | (0.006) | (0.005) | (0.008) |
| Others | -0.135\*\*\* | 0.059\*\*\* | 0.003 | -0.108\*\*\* | -0.427\*\*\* | -0.576\*\*\* | -0.352\*\*\* | -0.264\*\*\* |
|  | (0.008) | (0.007) | (0.008) | (0.009) | (0.008) | (0.008) | (0.007) | (0.010) |
| Constant | 0.244\*\*\* | 0.528\*\*\* | 0.696\*\*\* | 1.499\*\*\* | 0.342\*\*\* | 0.553\*\*\* | 0.864\*\*\* | 0.251\*\*\* |
|  | (0.017) | (0.014) | (0.015) | (0.023) | (0.017) | (0.018) | (0.015) | (0.027) |

Note: Detailed decomposition using recentered influence functions. Robust Standard Errors at Parenthesis. \*\*\* and \*\* indicate, respectively, p-value<0.01 and p-value < 0.05.

**5. Conclusion**

Sincenominal regional income disparities can just reflect regional price differentials, measuring effective regional disparities of income among localities impose a necessity of using income adjusted for local purchasing power differences. In this research, we used the recent local price indexes generated by Almeida and Azzoni (2016) for Brazilian metropolitan regions in order to measure and decompose the regional wage disparities between SP and the Brazilian northern metropolitan regions using RIF regression and Oaxaca-Blinder type decomposition. Thus, we are able to measure and decompose regional inequalities across wage distributions using values adjusted for regional purchasing power differentials, something unexplored in regional studies applied to the Brazilian context.

Two general important results were obtained and associated implications can be extracted. First, regional wage gaps vary both across quantiles and northern metropolitan regions, even after adjusting for local price differentials. Generally, the biggest regional wage gaps are found between SP and Belém (the smallest among the northern metropolitan regions), the smallest between SP and Salvador. Differently from the results obtained by Oliveira and Silveira Neto (2017) also for Brazil using macro regions but similarly to the results obtained by Galego and Pereira (2016) to Portuguese regions, wage gaps between SP and the Brazilian northern metropolis increase the higher the quantil of the wage distributions. Actually, differences are almost inexistent for the lowest quantiles (low-wage occupations) and significant for the highest quantiles (high-wage occupations). This implies that regional between SP and Brazilian northern metropolis hardly can be explained by lack of inter-regional mobility.

Second, both for intermediary and highest quantiles the individual characteristics of having a university degree (primarily) and being a black worker (secondarily) are important factors behind regional wages gaps and regional differentials related to economic activities play no relevant role. Actually, for highest quantiles factors associated with these two characteristics generally explain entirely regional wages gaps, which favor the idea of spatial equilibriums for these high-wage workers. Thus, traditional explanations for Brazilian regional disparities based on, for example, spatial concentration of the Manufacturing are not supported by our results. Interestingly, this result was also obtained both by Oliveira and Silveira Neto (2017) and Galego and Pereira (2016). On the other hand, our results suggest that the recent expansion of the Brazilian federal system of university and technical schools (during the 2000s) represented may help in reducing regional wage unbalance. Our results indicate that policies favoring race equality and labor formalization may also be able to contribute to reduce regional gaps.

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1. Professor do programa de pós-graduação em economia – UFBA. Pesquisador no Centro de Pesquisas em Economia Aplicada – UFBA e do Centro de Produção e Integração de Dados em Saúde (CIDACS). Rodrigo.coliveira13@gmail.com [↑](#footnote-ref-1)
2. Professor do Programa de pós-graduação em economia – PIMES/UFPE. Bolsista de Produtividade do CNPQ. Rau.silveira@uol.com.br [↑](#footnote-ref-2)
3. The others metropolitan regions with information available in PNAD are Rio de Janeiro and Belo Horizonte, also in the Southeast region, Curitiba and Porto Alegre, in the South region, and Brasília, in the Midwest region. [↑](#footnote-ref-3)
4. We use Epaminchov kernel with optimum bandwidth. [↑](#footnote-ref-4)
5. The estimative for women and for the other quantiles are available upon request. [↑](#footnote-ref-5)
6. The results for other quantiles are available upon request. [↑](#footnote-ref-6)