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Determinants of Income and Decomposition of Income Inequality by Gender, Ethnicity, and Residence in Pernambuco for the Years 2015 and 2019

Determinantes da Renda e Decomposição da Desigualdade de Renda por Sexo, Etnia e Residência em Pernambuco para os anos 2015 e 2019.

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Resumo: Este estudo examina os fatores que afetam a renda e a desigualdade de renda em Pernambuco, Brasil. Utilizando dados da PNAD Contínua, os autores estimam a equação minceriana para a renda e a decomposição de Oaxaca-Blinder com regressão quantílica incondicional. Os resultados mostram que a educação tem o maior impacto sobre os rendimentos, principalmente para indivíduos não brancos e do sexo feminino. Os efeitos inexplicados, como a discriminação, são os principais factores de desigualdade de rendimentos entre as zonas urbanas e rurais. Este estudo fornece informações valiosas sobre a distribuição do rendimento e sublinha a importância de abordar a educação e a discriminação nos esforços para reduzir a desigualdade.

Palavras-chave: Renda; Desigualdade; Educação; Discriminação.
Classificação JEL: D31; J15; I24.

Abstract: This study examines the factors affecting income and income inequality in Pernambuco, Brazil. Using data from the Continuous PNAD, the authors estimate the Mincerian equation for income and the Oaxaca-Blinder decomposition with unconditional quantile regression. The results show that education has the greatest impact on earnings, particularly for non-white and female individuals. Unexplained effects, such as discrimination, are the main drivers of income inequality between urban and rural areas. This study provides valuable insights into the distribution of income and highlights the importance of addressing education and discrimination in efforts to reduce inequality.

Keywords: Income; Inequality; Education; Discrimination.
JEL Classification: D31; J15; I24.

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1. Introduction

Income inequality gained prominence in academic studies in Brazil from the 1970s onwards, although this problem had been observed in the country since the colonial period. Studies carried out from the 1970s onwards pointed to a growing social inequality in all subsequent years, showing a point of inflection only from 1994 onwards (Araújo & Morais, 2014).

It was during the period known as the Brazilian "economic miracle" that began in the 1970s, which, in addition to bringing a high rate of economic growth and a significant gain in productivity to Brazil, the aforementioned continuous increase in inequality was observed, along with uncontrollable inflation (Prado, 2006).

The policies adopted during the Real Plan contributed to a trend of reducing inequality, as it had a positive and more intense impact on workers with lower levels of income. The policy of liberalizing foreign trade and a good agricultural harvest provided real gains for low-skilled labor, which resulted in a reduction in inequality, which in itself represents great importance, even though the government's central objective was inflation control (Rocha, 2000).

Until 1995, the Brazilian Northeast region had the highest social inequality accordingto the Gini Index among all Brazilian regions. From then until 2005, the cited region was the only one among all that presented an uninterrupted reduction in inequality, ceasing to be, at the end of this period, the region with the highest inequality, which then becomes the Central- West region (Berni, 2007).

According to Cavalcante (2020), Brazil presented a decreasing rate of income inequality until 2014, reaching a turning point in 2015 due to the persistent prolonged economic crisis that began in 2014.

Given this scenario, this article sought to study income inequality and income determinants for the years 2015 and 2019, the year preceding the onset of the pandemic. In those two years, the Northeast was the region with the highest Gini Index of Brazil (IBGE, 2022).

Among the nine states in the Northeast Region, the state of Pernambuco had the highest Gini Index value for the years studied, respectively presenting the values of 0.567 and 0.574, the second-highest Gini Index among the Federative Units of Brazil in the two periods studied, losing to the Federal District in 2015 and to Sergipe in 2019, which is why the state of Pernambuco is studied in this work IBGE (2022).

The objective of this article is to analyze how education, experience, gender, ethnicity, and place of residence affect income and how income inequality occurs by gender, ethnicity, and place of residence for Pernambuco in the years 2015 and 2019. To achieve this goal, we sought to evaluate the marginal effect of explanatory variables on individual income both on average and by quantiles, as well as to analyze the decomposition of income inequality by gender, ethnicity, and place of residence.

Since the period analyzed indicated a turning point in the previously observed continuous reduction in inequality since the Real Plan, this research contributed to evaluating the main factors that caused this differentiation of income for the state of Pernambuco, which had the highest Gini index in the observed period in the Northeast, a region already marked by strong inequalities.

Education was the variable that underwent the most changes among different income percentiles, and it is the one that best explains wage gains, especially for those with higher salaries. Unexplained factors, likely discrimination, were found to be the main drivers of the wage gap between white and non-white individuals. Women tend to have higher levels of education than men, which helps reduce the gender pay gap. However, women generally earn less than men because their education levels are not sufficient to offset the unexplained wage gap. For rural residents, income inequality decreases as income levels rise and approach thoseof urban residents.

Comparing 2015 to 2019, it was possible to note a greater marginal effect of quantitative variables, such as education and experience, on income in 2019, which explains the increase in average earnings over the period studied. In 2019, there was also a lower marginal effect of qualitative variables, such as location, indicating less wage differentiation on average between rural and urban areas, as well as between white and non-white individuals, and between men and women.

In addition to this introduction and the final considerations, this article consists of fouradditional sections. The second section describes the methodology and explains each econometric model used. The third section analyzes the data and examines the decomposition of income differences by gender, ethnicity, and location, identifying the effects of endowmentand discrimination for each group by percentile. Finally, the last section presents the concluding remarks.

2. Methodology

To achieve the proposed objectives, the present research is divided into two stages. Data from 2015 and 2019 were analyzed. The choice of 2015 is justified by observing a turning point in social inequality from that year, as there was a persistent decline in the Northeast since the FHC government. Since an unexpected shock caused by the effects of the pandemic affects income inequality in 2020, 2019 will be observed to evaluate the evolution of this data from 2015. For the years under study, Pernambuco was the Northeastern state with the highest value of the evaluated index. In the first stage, the main factors influencing individual salaries were analyzed through Mincerian equations, which were estimated for the mean of the data by Ordinary Least Squares and, for the quantiles of the income distribution, through unconditional quantile regressions. In the second stage, income inequality between gender, race, and location is analyzed through Oaxaca (1973) and Blinder (1973) type decomposition techniques combined with unconditional quantile regressions estimated in the previous stage.

The data used were obtained from the quarterly continuous PNAD, for the fourth quarter of each of the observed years, extracted and manipulated by the Stata program. The weight given by the survey to individuals was applied to the variables. Only individuals aged between 14 and 65 years were considered, as this is the age considered for the working-age population (PIA) according to Secchi (2002).

2.1. Wage Determinants in the State of Pernambuco

Initially, this study aims to analyze the main wage determinants of individuals residing in the state of Pernambuco in the years 2015 and 2019. To do so, this study used wage equations similar to those proposed by Mincer (1974) and estimated them using Ordinary Least Squares for the data means, as shown in equation (1).(1)(1)

$$\ln w = \beta\_0 + \beta\_1 * educ + \beta\_2 * exper + \beta\_3 * expersq + \beta\_4 * naobranco + \beta\_5 * mulher + \beta\_6 * Rural + \epsilon \quad (1)$$

In which:

lnw: The dependent variable that corresponds to the natural logarithm of the wages received by the individual; •

Educ: As a proxy for education, years of schooling will be used. According to Greene (2002), years of schooling can be used for this purpose, since the data available to researchers usually only include 'years of schooling'. •

Exper: This variable represents work experience measured in years. Age and age squared will be used as a proxy for work experience, as proposed by Patrinos (2016).

Expersq: Given that wages tend to decline with age, the variable expersq is used as the value of work experience squared.

Not-white: A qualitative variable that takes the value of 1 for self-declared non-white individuals and 0 for those who are self-declared white. This variable is important for analyzing income inequality, since due to the historical process of slavery in Brazil from colonial times until 1888, when slavery was finally abolished throughout the national territory, income has been more concentrated in the hands of white people (Maia & Silva, 2021).

Women: Since there is still much to achieve when it comes to gender pay equality, this variable will study the influence of sex on income inequality, using the value 0 for men and 1 for women.

Rural: Inequality presents itself differently between urban and rural areas. This variable will seek to identify the difference in wages between activities according to the space in which they occur, assigning a value of 1 for rural and 0 for urban.

However, it is important to emphasize that some factors that are statistically significant in influencing average salary earnings may not have the same influence throughout the entire income distribution. In this sense, to analyze the determinants of wages across the data distribution, Equation (1) was also estimated using Unconditional Quantile Regressions (UQR), proposed by Firpo et al. (2009).

2.2. Oaxaca-Blinder Method

The Oaxaca-Blinder method measures discrimination by estimating income for two groups of workers, which can be evaluated by ethnicity, gender, or even whether the activity is rural or urban. An equation is calculated for each possibility. The present study aims to analyze this for the rural sector, gender, and race. For this purpose, an income equation will be estimated for each group (rural and urban; non-white and white; female and male), LnWx and LnWy, respectively.

$$LnWx = \beta r X'x + \epsilon x \quad (2)$$

And

$$LnWy = \beta u X'y + \epsilon y \quad (3)$$

Where W, X, and ϵ are the income, set of explanatory variables, and the random error term, respectively.

Afterward, it is necessary to decompose the differential, obtaining equation (4):

$$Ln\bar{W}y - Ln\bar{W}x = (\bar{X}y - \bar{X}x) * \bar{\beta}x + \bar{X}y * (\bar{\beta}y - \bar{\beta}x) \quad (4)$$

$(\bar{X}y - \bar{X}x) * \bar{\beta}x$ is part of the differential attributed to discriminatory characteristics, that is, those that are not productive, and is referred to as the "discrimination effect". While $\bar{X}y * (\bar{\beta}y - \bar{\beta}x)$ is the part of the differential that is attributed to discriminatory characteristics, that is, that are not productive, called “discrimination effect”,

The study will use three different equations similar to equation (4)(4)(4), one comparing rural to urban, another considering ethnicity, and one more on gender.

3. Results

According to the Gini index, table 1, the state of Pernambuco showed an increase in income inequality between the years 2015 and 2019. During this period, among the Northeastern states, it had the highest level of inequality.

Table 1: Gini index from 2015 to 2019: Brazil, Northeast, and Northeastern states

	2015	2016	2017	2018	2019
Brazil	0,524	0,537	0,539	0,545	0,544
Northeast	0,533	0,544	0,557	0,546	0,560
Maranhão	0,495	0,517	0,526	0,528	0,531
Piauí	0,520	0,528	0,529	0,530	0,537
Ceará	0,528	0,543	0,547	0,547	0,562
Rio Grande do Norte	0,518	0,543	0,523	0,540	0,554
Paraíba	0,531	0,527	0,548	0,549	0,561
Pernambuco	0,567	0,567	0,551	0,534	0,574
Alagoas	0,525	0,523	0,525	0,550	0,527
Sergipe	0,539	0,567	0,551	0,578	0,581
Bahia	0,522	0,539	0,590	0,550	0,557

Source: IBGE (2022).

3.1. Mincerian Equation for Pernambuco in 2015 and 2019

To begin understanding the factors that affect wage levels, we estimated a regression using the OLS model as already detailed in the methodology for the year 2015, according to Table 2. Robust standard errors are used in this regression.

One can observe a positive correlation between salary and the variables: education and experience. As expected, the variable expersq, used as a correction factor for the effect of experience on income, showed a negative correlation, indicating a decreasing marginal effect. Regarding the variables that capture inequalities between attributes, all showed a negative correlation with salary, following the results found in the theory that women, non-whites, and residents in rural areas have lower remuneration.

Among the quantitative variables, education had the greatest marginal effect on income. This is consistent with the study by Silveira et al. (2015), which evaluated the effect of education on income in Brazil, indicating that the positive effect of education, as in the country, is repeated for the state of Pernambuco.

Table 2: Mincerian Equation for 2015

Variable	Constant	Educ	exper	expersq	naobranco	mulher	rural
Coefficient	4,705	0,106	0,06	-0,001	-0,199	-0,356	-0,442
Prob	0,000	0,000	0,000	0,000	0,000	0,000	0,000

Source: Prepared by the authors based on PNADC data from 2015.

When estimating the regression for the year 2019, according to table 3, the correlation between the explanatory variables and salary presented the same direction as the correlation observed in 2015, following the expected pattern according to theory. However, it is worth noting that both educ and exper variables had a greater marginal effect on salary in 2019. This means that an increase in education level or experience, all else being constant, resulted in a higher salary in 2019 than in 2015.

Additionally, it can be observed from the regression coefficients that there was a reduction in the salary difference between the variables that capture inequalities between attributes, with a greater emphasis on the fact that the salary difference between rural and urban areas decreased the most over time, although in 2019, rural residents still earned 28.97% less than those living in urban areas, ceteris paribus. Women showed the least reduction in salary differences with men over time. Non-whites reduced the salary gap with whites, all else being constant, from 18.08% in 2015 to 13.82% in 2019.

Table 3: Mincerian Equation for 2019

Variable	Constant	educ	exper	expersq	naobranco	mulher	rural
Coefficient	4,187	0,117	0,0812	-0,001	-0,149	-0,354	-0,342
Prob	0,000	0,000	0,000	0,000	0,000	0,000	0,000

Source: Prepared by the authors based on data from the 2015 PNADC.

3.2. Unconditional Quantile Regression for the State of Pernambuco, 2015 and 2019

When studying the wage level, the value of the marginal effect of each explanatory variable on income fluctuates according to the observed quantile, justifying the use of quantile regression.

The conditional quantile regression estimates the return of certain individual characteristics, holding everything else constant so that such a return varies according to the observed quantile. Unconditional quantile regressions, on the other hand, provide an estimate of the effect of small changes in an individual's characteristic for each quantile, allowing for the evaluation of the effect on a wide range of income distribution statistics, holding everything else constant (Silva & França, 2016). In addition, it is possible to use the inference functions calculated for each quantile in the calculation of the Oaxaca-Blinder decomposition method, as already described in the methodology.

When estimating the unconditional quantile regression for the 0.10, 0.25, 0.50, 0.75, and 0.90 quantiles for the same variables in the previously estimated Mincerian equation for the years 2015 and 2019, the following coefficients are obtained for each quantile according to Table 4.

It is observed that, for both analyzed periods, the coefficient of the non-white variable for the 0.10 quantile and the coefficient of the rural variable for the 0.90 quantile are the only ones that are not significant.

Years of schooling or experience resulted in a positive effect on income in all quantiles, regardless of the observed year. It is also worth noting that, for all significant coefficients, the effect of variables that capture inequalities between attributes had the same direction in all quantiles as presented in the Mincerian equation estimated by OLS, and it was observed that, regardless of which quantile it is located in, women, non-whites, or residents of rural areas have lower wages.

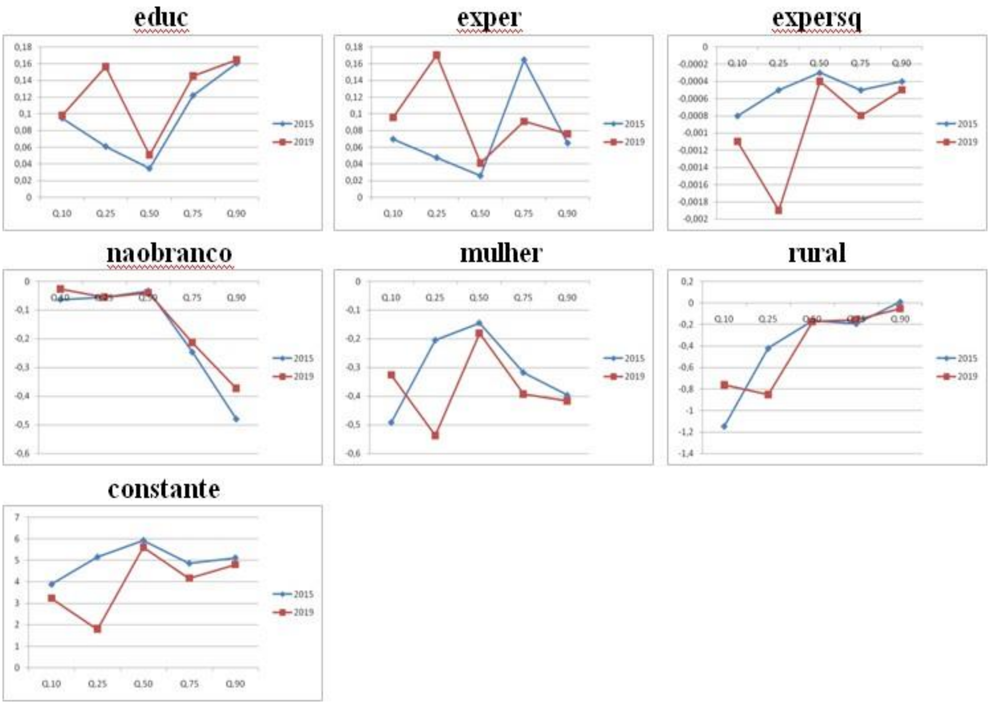
Table 4: Unconditional Quantile Regression of the Mincerian Equation for Pernambuco in 2015 and 2019

2015	**Quantil 0.10**	**Quantil 0.25**	**Quantil 0.50**	**Quantil 0.75**	**Quantil 0.90**
Educ	0,095*	0,061*	0,035*	0,122*	0,160*
Exper	0,069*	0,047*	0,026*	0,165*	0,065*
Expersq	-0,001*	-0,001*	-0,000*	-0,001*	-0,001**
Not white	-0,063	-0,056*	-0,033*	-0,2471*	-0,481*
Women	-0,491*	-0,204*	-0,144*	-0,317*	-0,396*
Rural	-1,146*	-0,421*	-0,167*	-0,191*	0,009
Constant	3,882*	5,158*	5,931*	4,862*	5,119*
2019	**Quantil 0.10**	**Quantil 0.25**	**Quantil 0.50**	**Quantil 0.75**	**Quantil 0.90**
Educ	0,098*	0,156*	0,050*	0,145*	0,164*
Exper	0,095*	0,170*	0,041*	0,091*	0,076*
Expersq	-0,001*	-0,001*	-0,000*	-0,000*	-0,000*
Not white	-0,025	-0,054	-0,038*	-0,213*	-0,373*
Women	-0,325*	-0,536*	-0,180*	-0,392*	-0,416*
Rural	-0,761*	-0,851*	-0,174*	-0,153*	-0,050
Constant	3,238*	1,786*	5,611*	4,160*	4,796*

Source: Prepared by the authors based on data from the 2015 PNADC.
* Significant at 1%. ** Significant at 5%.

For a better evaluation of the effect of each explanatory variable by observed quantile, an analysis of Figure 1 allows for a better assessment. Unlike the result identified by Souza et al (2022) when studying the Mincerian equation in Brazil by quantile regression in 2015, the effect of education was lower in the estimate for the median (0.50 quantile), while in the referred work, the marginal effect was strictly increasing.

Figure 1: Marginal effect of each variable by quantile for 2015 and 2019



Source: Prepared by the authors based on data from the 2015 and 2019 PNADC.

In 2015, the education variable showed a decreasing behavior between the 0.10 and 0.50 quantiles, starting from then on a growth that extends up to the 0.90 quantile. For 2019, education was highly influential in salary for the 0.25 quantile, with a considerable increase between the first two observed quantiles. It is possible to identify that education has a great effect on income in the 0.75 and 0.90 quantiles, as well as the 0.10 quantile, regardless of the evaluated year. The 0.50 quantile is where the smallest effect of education on income is observed.

The behavior of the exper variable observed in graph of the figure 1 is similar to what can be found in education, except for the 0.90 quantile, where a new setback is observed, indicating that experience has little effect on the remuneration of higher income classes.

Non-white people have a similar remuneration to whites among the lower quantiles, oscillating a little between 0.10 and 0.50. As one moves towards the higher quantiles, it is possible to identify a greater wage gap between whites and non-whites, where the latter receive much less than the former. This fact corroborates with Prata's research (2009), which points to a greater wage gap between whites and non-whites for the higher quantiles.

The 0.50 quantile is where the wage gap between men and women is smaller, expanding from there to the upper quantiles. Comparing 2015 to 2019, the great difference in the 0.25 quantile stands out, where in 2015 it represents the second highest coefficient value, while in 2019 is where there is a greater wage gap between men and women. The study conducted by dos Santos (2017) resulted in a greater difference for the median when only the metropolitan region of Salvador was studied, differing from the result of this research, indicating that this difference between quantiles is not homogeneous among localities.

As income increases, the wage gap decreases between urban and rural residents. Therefore, the greatest difference can be found in the first two evaluated quantiles.

3.3. Quantile Decomposition of the Unconditional Quantile Regression of the Mincerian Equation for Pernambuco in 2015 and 2019

The inequality decomposition using a combination of the Unconditional Quantile Regression with the Oaxaca-Blinder method has the advantage of performing a decomposition of wages for each observed quantile, thus identifying whether there is a predominance of the endowment effect or the discrimination effect. In this study, the decomposition was performed for each qualitative variable, namely: rural, non-white, and female.

For the rural area, as presented in Table 5, the discrimination effect predominated. In all observed quantiles and for both years, the endowment effect had a non-significant coefficient. The discrimination effect only had a non-significant value in the 0.50 quantile of 2019, being significant at 5% in the 0.75 quantile of 2019. The 0.10 quantile of 2015 had a variance equal to zero in the endowment effect, resulting in the impossibility of calculating the significance for group 1 (Rural). The remaining coefficients were significant at 1%.

Table 5: Quantile Decomposition of the Unconditional Quantile Regression of the MincerianEquation for Pernambuco between rural and urban areas in 2015 and 2019

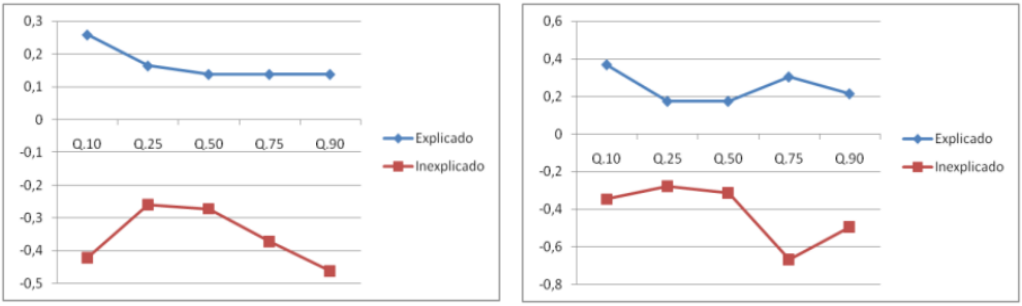
2015	**Quantil 0.10**	**Quantil 0.25**	**Quantil 0.50**	**Quantil 0.75**	**Quantil 0.90**
Rural	3,224	3,434*	3,632*	3,752*	3,804*
Urban	3,731*	3,947*	4,121*	4,407*	4,491*
Difference	-0,506*	-0,513*	-0,489*	-0,655*	-0,686*
Explained	0,000	-0,084	-0,084	-0,122	-0,122
Unexplained	-0,506*	-0,428*	-0,404*	-0,532*	-0,563*
2019	**Quantil 0.10**	**Quantil 0.25**	**Quantil 0.50**	**Quantil 0.75**	**Quantil 0.90**
Rural	3,089*	3,275*	3,463*	3,967*	4,052*
Urban	3,699*	4,056*	4,263*	4,504*	4,664*
Difference	-0,609*	-0,781*	-0,799*	-0,537*	-0,611*
Explained	-0,012	-0,012	-0,487	-0,187	-0,187
Unexplained	-0,597*	-0,768*	-0,312	-0,349**	-0,424*

Source: Prepared by the authors based on PNADC data from 2015 and 2019.
* Significant at 1%. ** Significant at 5%.
*

A graphical analysis of the difference between urban and rural areas shows that for the lower quantiles, from 0.10 to 0.50, the difference between rural and urban areas was greater in 2019. In 2019, the difference decreased from the 0.50 quantile, becoming lower than in 2015 when comparing both by the 0.75 and 0.90 quantiles. Although smaller than in 2015, in 2019, for the 0.90 quantile, the difference increases compared to the previously observed quantile, as highlighted in Figure 2.

Figure 2: Endowment and discrimination effects on income between men and women, 2015and 2019

2015 **2019**



Source: Prepared by the authors based on PNADC data from 2015 and 2019.

The fact that the graphical behavior for the difference and the unexplained effect is similar, where the coefficients were significant, allows the inference that it was the variablesthat capture inequalities between attributes that most justify the lower gain of rural workers compared to urban workers, which may explain the non-significance of the dotation effect coefficient in the difference. It is also worth noting that in 2019 the gap between urban and rural areas decreases from the 0.75 quantile, a phenomenon that is opposite to what was observed in 2015.

The discrimination effect is weaker in 2015 for the first two quantiles studied, while for the two highest-paying quantiles, such effect increased in 2015. Contrary to this trend in 2015, in 2019 the discrimination effect is higher in the initial quantiles and shows a considerable reduction from the 0.50 quantile, being lower than in 2015 from that point on.

Table 6 points to a strong wage gap between men and women, which is not justified by explained factors. This finding is supported by the fact that the endowment effect showed a positive value, mainly influenced by the variable of education, while the discrimination effect fluctuated between -0.2598 and -0.6675.

Table 6: Decomposition of the unconditional Quantile Regression of the Mincerian equationfor Pernambuco between women and men, 2015 and 2019.

2015	Quantil 0.10	Quantil 0.25	Quantil 0.50	Quantil 0.75	Quantil 0.90
Woman	3,464*	3,749*	3,942*	4,046*	4,108*
Man	3,627*	3,845*	4,077*	4,280*	4,433*
Difference	-0,163	-0,096	-0,135	-0,234**	-0,325*
Explained	0,258*	0,163*	0,137*	0,137*	0,137*
Unexplained	-0,422**	-0,259*	-0,272**	-0,372*	-0,462*
2019	**Quantil 0.10**	**Quantil 0.25**	**Quantil 0.50**	**Quantil 0.75**	**Quantil 0.90**
Woman	3,305*	3,913*	4,109*	4,253*	4,384*
Man	3,375*	4,016*	4,248*	4,616*	4,665*
Difference	-0,070	-0,102	-0,139	-0,362*	-0,280*
Explained	0,369*	0,174*	0,174*	0,304*	0,215*
Unexplained	-0,346	-0,277**	-0,314	-0,667*	-0,495*

Source: Prepared by the authors based on PNADC data from 2015 and 2019.
* Significant at 1%. ** Significant at 5%.

Over the years, it has been observed that the endowment effect has become even greater. It is worth noting the effect for the 0.10 and 0.75 quantiles in 2019, which showed the highest values in the series. In 2015, the value of the endowment effect was the same for the three highest quantiles analyzed in Figure 2.

Regarding the discrimination factor, the lowest values are found in the 0.25 and 0.50 quantiles. In 2019, the emphasis should be placed on the high value of this effect for the 0.75 quantile. It is possible to observe that the difference between the endowment effect and the discrimination effect is greater in the 0.10 quantiles and in the 0.75 and 0.90 quantiles.

The salary income for women is lower than for men. This gap can be observed despite the endowment effect having a positive sign. As observed in the study by de Jesus, Silva and Neves (2020), this is because women, although having a higher average level of education, still earn less on average than men.

This study presents results of such decomposition in line with most empirical research, as in the case of the study by Paschoalino, Plassa and dos Santos (2017), who, by decomposing the income difference between men and women in Brazil in 2015 using the Oaxaca-Blinder method, found that men earned more than women, with a wage gap of 12.46%. Such a study also points to a positive endowment effect.

Upon analyzing Table 7, it is inferred that the discrimination effect is only significant at 5% in the 0.75 quantile of the year 2019, and is not significant for the other estimated coefficients. The endowment effect is what has the greatest impact on the wage gap between white and non-white individuals, with education being the factor that explains lower remuneration for non-white individuals. The 0.10 quantile of the year 2019 had all its coefficients, except for the non-white coefficient, as not significant, making it impossible to make any conclusions about this specific quantile.

Table 7: Decomposition of the Unconditional Quantile Regression of the Mincerian Equationfor Pernambuco between Non-White and White for 2015 and 2019

2015	**Quantil 0.10**	**Quantil 0.25**	**Quantil 0.50**	**Quantil 0.75**	**Quantil 0.90**
Not white	3,511*	3,777*	3,980*	4,106*	4,186*
White	3,689*	3,817*	4,001*	4,154*	4,389*
Difference	-0,178	-0,039	-0,020	-0,047	-0,202
Explained	-0,089*	-0,075*	-0,097*	-0,128*	-0,128*
Unexplained	-0,089	0,035	0,077	0,081	-0,073
2019	**Quantil 0.10**	**Quantil 0.25**	**Quantil 0.50**	**Quantil 0.75**	**Quantil 0.90**
Not white	3,424*	3,935*	4,128*	4,398*	4,478*
White	3,242	4,038*	4,422*	4,662*	4,707*
Difference	0,182	-0,102	-0,293	-0,263*	-0,228*
Explained	-0,047	-0,054*	-0,054*	-0,097*	-0,097*
Unexplained	0,229	-0,048	-0,239	-0,166**	-0,131

Source: Prepared by the authors based on PNADC data from 2015 and 2019.
* Significant at 1%. ** Significant at 5%.

Conclusion

The average salary level of residents in Pernambuco has been increasing between 2015 and 2019, while the wage gap between white and non-white workers, as well as between rural and urban residents, has been decreasing. Education is the variable with the greatest marginal effect on income.

When evaluating the Unconditional Quantile Regression, it was possible to identify that, for lower-income classes, the effect of experience and education on income is similar. As income increases, education has a greater influence on income, making it the variable that explains the most significant difference in income.

According to the Unconditional Quantile Regression data, the effect of being non-white on income is more significant as it reaches higher quantiles, such as 0.75 and 0.90. For lower quantiles, those with lower income levels, the behavior is almost constant, meaning that there is no distinction or little distinction between white and non-white workers.

Women have lower wages than men in the most extreme social classes, regardless of their income level. In the 0.50 quantile, which represents the median income level of the population, we find the smallest wage gap between men and women.

The rural area only strongly influences lower-income classes. As we evaluate higher quantiles, we observe a significant reduction in this influence on wages. In this territorial space, the predominant effect is discrimination, which is stronger in 2019 and for lower quantiles.

The income decomposition for women highlighted that the endowment effect for women is positive, directly influenced by the education variable. This indicates that women have a higher level of education than men, resulting in a reduction in the wage gap with male workers. Nonetheless, women still receive lower wages because the discrimination effect is negative, and its magnitude is greater than the endowment effect, which means that even with higher education, women earn less than men. For non-white workers, contrary to expectations, the predominant effect is the endowment effect, and the discrimination effect is insignificant in almost all observed quantiles.

Education is also the variable that explains the wage gap between white and non- white workers, indicating the significant role of education in all stages of the research. As education is the variable that can most significantly increase the level of remuneration and explain income inequality, this study suggests that investment in education by public policies could not only reduce social and historical inequality but also increase the standard of living of residents in Pernambuco.

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