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Does Investing in Education Reduce the Gender Wage Gap? A Brazilian Population Study

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Abstract

The main purpose of this paper is to identify the existence of wage discrimination between men and women, focusing on people holding college degrees, which has the potential for a higher gap since it depends not only on qualification but also on promotion rates in the job market. Using public data from National Household Sample Survey (PNAD, IBGE) from 2007 to 2009, we identify the key factors for wage determination due to demographic characteristics and to labor attributes. Then, we quantify how much of the wage discrepancy is explained for each of these personal and job related characteristics using the Ordinary Least Squares and the Quantile Regressions approach, both in a Oaxaca-Blinder set up. The unexplained differences from these estimations are attributed to sex discrimination. The results show that the gender wage gap tends to be higher for individuals who hold a college degree than for the average population (around 54% for the former and 16% for the latter), and that the main salary discrepancies are neither explained by personal characteristics nor by the distinct career paths, suggesting that in the business sector, particularly with regard to high level positions, women face barriers to advancement.

Keywords

Gender wage gap, discrimination, quantile regression, Brazil

1. Introduction

In Brazil, the recent increased participation of women in the labor market and improved conditions for women's employability is remarkable. Boosted by the "economic miracle" (1968-1973), the 1980s can be considered a turning point for the greater inclusion of women in the labor market. Although there was no consistency in the economic acceleration after this period, the following decades maintained the trend of an increased participation of women in the labor market, and men continued to make up the great majority of the labor force, as shown in the table below with data from the Brazilian Institute of Geography and Statistics (*Instituto Brasileiro de Geografia e Estatística – IBGE*). As shown in Table 1, IBGE has found that 13% of working-age women participated in the labor market in 1950, whereas 53% of working-age women were part of the economically active population in 2010.

Table 1 – Labor market participation of men and women in Brazil

	1950	1960	1970	1980	1990	2000	2010
Men	82%	77%	72%	72%	72%	70%	70%
Women	13%	18%	19%	27%	35%	44%	53%

Source: Statistics of the Twentieth Century for 1950 and 1960 and the Brazilian Institute of Geography and Statistics' Demographic Censuses for 1970, 1980, 1990, and 2000. Brazilian Institute of Geography and Statistics (IBGE) considers economic actively age beginning at 10 years old.

Participation in the labor market is highly related to education level, and participation in the labor market increases with years of education. The National Household Sample Survey (*Pesquisa Nacional por Amostra de Domicílios – PNAD*) in 2009 showed that, among women in the working-age, only 34% of women with no schooling were engaged in the labor force, whereas 82% of women with higher education were either working or seeking work.

As female participation in the labor market has increased significantly, the gender wage gap has decreased in Brazil. In the early 1990s, the income discrepancy between men and women was 50%, decreasing to around 30% at the beginning of the year 2000 (Madalozzo and Martins 2007). However, an equivalent reduction did not occur for people with higher education. The result of the Annual List of Social Information (*Relação Anual de Informações Sociais – RAIS*) of the Ministry of Labor, in 2010, showed that, for all education levels, women received lower wages than men and that the wage gap was positively correlated with education level. Although, on average, women received a 17.2% lower average wage than men, this difference increased to 40.8% for women who hold college degrees.

Women thus still face difficulties in receiving compensation equal to that received by men. Different demographic characteristics (Loureiro, Carneiro and Sachshida 2004; Garcia, Nopo and Salardi 2009), workload selections (Marri and Wajnman 2005), and occupation choices (Braga 2007; Madalozzo 2010) between men and women contribute to this wage gap. These choices depend on the intellectual capacity of the individuals, their qualifications and preferences (Soares 2000; Haag and Schockmel 2003), and the social acceptance of their choices (Ferber 1993).

The present research contributes to the gender gap discussion, focusing on people holding college degrees. Education means both a social and private investment (Van der Merwe 2010), and people who attain college degrees are the ones who received the highest investment. They were selected to hold a college degree because they were either more intellectually able or because they were more persistent than the rest of the population to obtain a degree. For either one of these reasons, these individuals spent more time studying to pursue better jobs and remuneration. Understanding the gender gap in this target population means to highlight the differences on gender treatment among the most talented individuals and to learn how to avoid wasting this investment (Hewlett, Luce and Servan 2008).

We use a decomposition approach (Oaxaca 1973; Blinder 1973) for linear and quantile regression of mincerean wage equations. Our goal is to estimate the wage profiles for men and women and compare their unexplained differences on average – using the linear regression approach – and for different points of conditional distribution – using the quantile approach (Koenker and Bassett 1978). Our results point to the existence of gender wage gap among college degrees holders in Brazil and, therefore, to potential discrimination factors that may endanger women's choices on their human capital investment and personal expectations.

The present article is organized as follows. In part 2, we describe the methodologies used for data analysis, focusing on the underlying concepts and premises for each method. Part 3 provides the data description, descriptive statistics, analysis and interpretation. Part 4 concludes the article.

2. Methodology

Understanding the wage gap needs to consider both the individual as well the market effect on the formation of wages. On this point, our methodological approach followed the traditional decomposition of Oaxaca (1973) and Blinder (1973). However, we chose to include two different methodologies for wage estimation: ordinary linear regression, that measures the effect on its average, and the quantile regression, that distinguishes the effects depending on its conditional distribution. The goal of the present section is to present the methodological approaches.

2.1 Decomposition method using linear regression

Mincer (1970) proposed an analysis to control for the different influences of each individual's characteristic on his/her wage formation. To this end, the logarithm of an individual's hourly wage is explained by his/her personal characteristics, such as age and years of education, his/her work profile, including years of experience, and his/her occupation. Traditionally, linear regressions of wages were summarized as follows:

$$\ln w_i = \alpha + \sum_{j=1}^{l} \beta_j X_i + \sum_{k=1}^{m} \gamma_k Z_i + \varepsilon_i , \qquad (1)$$

where wi is the individual's hourly wage, Xi represents the individual characteristics and work profile, and Z_i is the individual's occupation detailed by dummy variables.

The Oaxaca (1973) and Blinder (1973) decomposition was based on separate linear regressions for men and women in the target population.

$$\text{Ln}\,\hat{w}_i^H = \hat{\alpha}^H + \sum_{j=1}^{k} \hat{\beta}_j^H X_i^H + \sum_{l=1}^{m} \hat{\gamma}_l^H Z_i^H \qquad (2)$$

$$\ln \hat{w}_i^M = \hat{\alpha}^M + \sum_{j=1}^{k} \hat{\beta}_j^M X_i^M + \sum_{l=1}^{m} \hat{\gamma}_l^M Z_i^M \qquad (3)$$

Equation (2) estimated the coefficients of the male' sample of the population and equation (3) estimated the same, only for the females. The Oaxaca-Blinder decomposition divided the wage gap into two parts. The first part can be explained by personal characteristics, work profiles, and occupational choices. The second part of the decomposition deals with the wage difference unexplained by these characteristics, thus representing discrimination. Some variables reflecting characteristics are already biased by the choices that individuals make, causing their labor to be

priced differently in the labor market. The premise of a linear regression – a method usually employed to estimate wage decomposition – is that each variable, such as age or education, has the same effect on earnings at all income distribution points; thus, only the average effect of each variable is considered. In order to account for the conditional distribution of wages, we proposed the use of the quantile regression model as an alternative.

2.2 Quantile regression method

The quantile regression model was proposed by Koenker and Bassett (1978). This method improves the standard linear regression because it allows for an analysis of the conditional influence of explanatory variables at different income distribution points. The influence of each variable can be quantified using this technique. In addition to measuring the average explanation, we were able to identify the influence of each variable, distinguishing for individuals with lower and higher incomes. Instead of minimizing the sum of squared errors, as in linear regression, quantile regression minimizes the sum of absolute errors, proposing different weights for the observations depending on their conditional location and the quantile the regression aims at.

We defined each quantile as a linear function of the model:

$$\min_{\xi \epsilon R} \sum \rho_{\tau} \left(y_i - \xi(x_i, \beta)\right), \qquad (5)$$

where τ indicates the conditional quantile of the log of the hourly wage for each individual at each explanatory variable. To estimate the function of the first conditional quantile, we substituted τ with $\frac{1}{4}$, and to estimate the function of the conditional median, we substituted τ with $\frac{1}{2}$. We thus were able to estimate the partial derivative of any variable, including age, education, and occupational choices to discover its influence on wages. This effect might be different for each quantile (Koenker and Hallock 2001).

3. Data analysis

The present analysis used the National Household Sample Survey (*Pesquisa Nacional por Amostra de Domicílios – PNAD*), an annual survey conducted by the IBGE. Because we worked exclusively with people with higher education, whose representation was approximately 6% of the Brazilian resident population, we aggregated the PNAD samples for the years 2007, 2008, and 2009 to provide more observations for analysis.

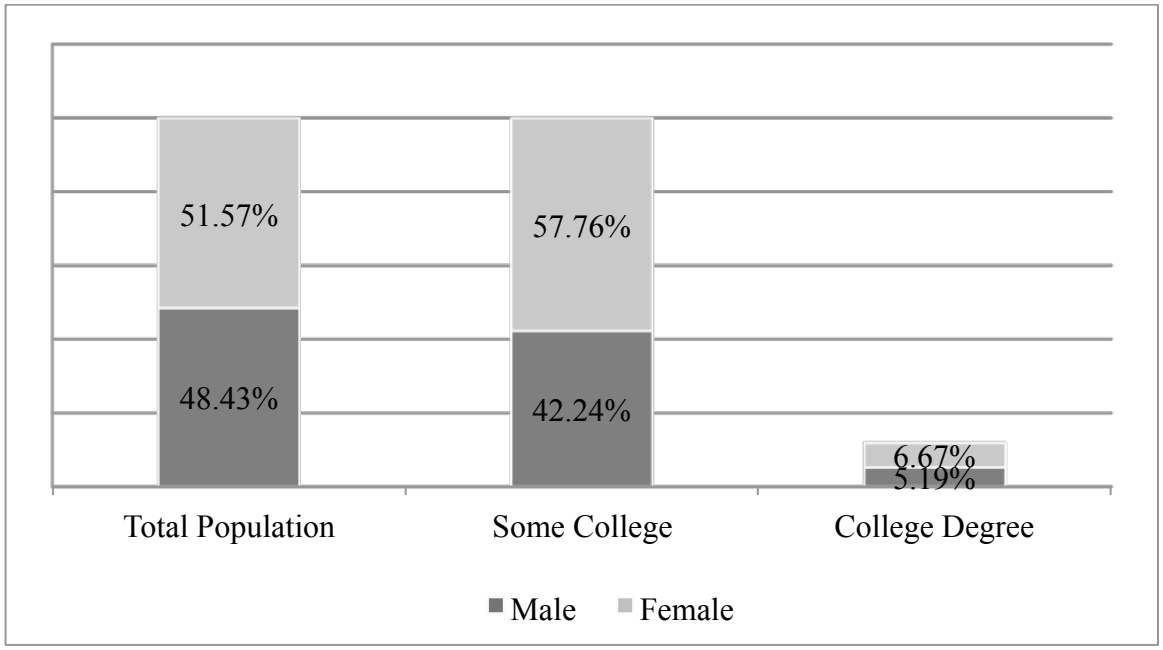
A demographic analysis of the variables of interest for the data from 2007, 2008, and 2009 was initially performed to highlight the differences between female and male characteristics.

3.1 Descriptive analysis

Based on PNAD data from 2009, Figure 1 shows that whereas 48.43% of the population is male, only 42.24% of the sample that has completed at least one college degree is male, indicating that women have a higher rate of engagement on higher education than men. At the same time, completion rates differ among genders. More women (6.67%) than men (5.19%) completed college. This observation shows that women have, on average, better education than men. .

On average, the population is 41.52 years old; men are slightly older than women (42.77 compared to 40.57), with no statistical difference for this difference. Men spend more time on labor market activities than women (41.23 against 36.18 hours per week); however, women spend more hours on housework (19.14 hours per week) than men (8.86 hours per week). These results are comparable to international literature on women, which shows that women are engaged in more hours in housework than men (Hersch and Sttraton 1994, 2002).

Figure 1: Gender and Population Distribution, College Degrees Attainment. Brazil (2007 to 2009)



Source: PNAD 2009. Authors' tabulation.

Table 2 presents data from PNAD 2007, 2008, and 2009 for individuals holding college degrees. Our target variable is the wage gap. Table 2 presents the first result on this subject: without any control, men earn, on average 54.37% more than women. This is a very high difference, however, because it is not controlling for individual characteristics, it may be misleading. The remainder of this research analyses this question deeply.

Table 2: Demographic variables for college degrees holders, comparison between genders

Demographic Variable	Total	Men	Women
Mean age	41.52 (13.36)	42.77 (13.95)	40.57 (12.83)
Hours spent in the labor market	38.48 (11.89)	41.23 (11.79)	36.18 (11.48)
Hours of housework	15.83 (13.35)	8.86 (7.59)	19.14 (14.20)
Average hourly wage in Brazilian reais (R$)	22.86 (50.59)	28.28 (54.55)	18.32 (46.53)
Number of observations	43,381	13,555	29,826

Source: PNAD 2007, 2008, and 2009. Authors' tabulation.
Wages, in Brazilian reais (R$), were adjusted using the National Consumer Price Index (Índice Nacional de Preços ao Consumidor Amplo – IPCA – base year 2009).

3.1.1 Race

Based on PNAD data, Table 3 shows the proportion of the population of college degree holders by race using their own declaration. The majority of respondents (75.30%) declared themselves Caucasian, followed by Mixed race (19.55%). Gender distribution was very close to the total distribution concerning race. A higher proportion of men declared to belong to the Caucasian race than women (76.22 against 74.61% of women). The opposite happened for Mixed race (18.21% of male and 20.56% of female).

Table 3: Race description for college degrees holders, comparison between genders

Race	Total (%)	Men (%)	Women (%)
Asian descent	1.65	1.91	1.45
Caucasian	75.30	76.22	74.61
Indigenous	0.15	0.13	0.16
Black	3.35	3.53	3.22
Mixed race	19.55	18.21	20.56
# Observations	53,346	24,080	29,266

Source: PNAD 2007, 2008, and 2009. Authors' tabulation.

Table 4 shows that people who claimed to be Caucasian had the highest average hourly wages (R$ 24.28) and those claiming to be Black had the lowest average hourly earnings (R$ 17.93). Wider gender-based wage gaps occur among the Caucasian (55.62%), Black (48.36%), and Mixed race populations (47.66%), and the smallest gap is found in the Asian descents (26.51%). Table 4 shows no significant difference of gender wage among Indigenous individuals holding college degrees.

Table 4: Hourly wage (in Brazilian reais, R$) description for college degrees holders, comparison between genders

Race	Total	Men	Women	Difference (%)
Asian descent	23.23 (31.09)	25.82 (28.04)	20.41 (33.92)	26.51 (*)
Caucasian	24.28 (54.47)	30.05 (57.50)	19.31 (51.19)	55. 62 (***)
Indigenous	19.47 (24.29)	18.34 (15.24)	20.19 (29.32)	-9.16
Black	17.93 (30.41)	21.69 (36.92)	14.62 (22.74)	48. 36 (***)
Mixed race	18.45 (38.05)	22.68 (46.08)	15.36 (30.55)	47.66 (***)
# Observations	53,346	24,080	29,266	

Source: PNAD 2007, 2008, and 2009. Authors' tabulation.
Wages were adjusted using the IPCA (base year 2009).
(***) Significant at 1%, (**) significant at 5%, and (*) significant at 10%.

3.1.2 Public and private sector

As the PNAD data in Table 5 shows, there is a similar distribution of people holding college degrees on private and public sectors. Women are concentrated more in the public sector and men, in the private sector. Table 6 shows that, on average, the public sector provides better wages than the private sector, and that the wage difference between men and women is slightly higher in the public sector. Men working in the public sector receive a 63% higher average hourly wage than women, whereas men working in the private sector have average hourly earnings that are 61% higher than those of women in the same sector.

Table 5: Private and Public Sector work distribution for college degrees holders, comparison between genders

Sector	Total (%)	Men (%)	Women (%)
Private	50.55	59.23	44.28
Public	49.45	40.77	55.72
# Observations	40,895	17,015	23,880

Source: PNAD 2007, 2008, and 2009. Authors' tabulation

Table 6: Hourly wage (in Brazilian reais, R$) profile for college degrees holders, comparison between genders

Sector	Total	Men	Women	Difference (%)
Public	22.66	30.36	18.59	63.31 (***)
	(31.24)	(41.47)	(23.13)	
Private	19.52	24.16	15.04	60.64 (***)
	(43.79)	(57.65)	(22.79)	
# Observations	40,895	17,015	23,880	

Source: PNAD 2007, 2008, and 2009. Authors' tabulation.
Wages were adjusted using the IPCA (base year 2009).
(***) Significant at 1%, (**) significant at 5%, and (*) significant at 10%.

3.1.3 Housework indicator

Table 7 shows the percentage of the population with a higher education that has a domestic workload. 68.29% of college degrees holders perform some housework during a week. This percentage shows a high variation between genders: 51% of men do housework as compared to 81% of women.

Table 7: Housework profile for college degree holders, comparison between genders

Housework	Total (%)	Men (%)	Women (%)
Yes	68.29	51.03	81.37
No	31.71	48.97	18.63
# Observations	53,346	24,050	29,296

Source: PNAD 2007, 2008, and 2009. Authors' tabulation.

Table 8 compares the hourly wage for people according their housework indicator. People with higher education and no domestic workload have higher average hourly wages than those who do some housework. Also, the gender wage gap is smaller for individuals who do not perform housework. The hourly wage of men with housework is 54.84% higher than that of women with housework, and the gap is 39.46% for those without housework. These wage gaps are statistically significant.

Table 8: Housework profile and hourly wage (in Brazilian reais, R$) for college degree holders, comparison between genders

Housework	Total	Men	Women	Difference (%)
Yes	21.03	27.36	17.67	54.84 (***)
	(51.39)	(55.72)	(48.60)	
No	26.55	29.23	20.96	39.46 (***)
	(48.74)	(53.30)	(36.81)	
# Observations	53,346	24,050	29,296	

Source: PNAD 2007, 2008, and 2009. Authors' tabulation.
Wages were adjusted using the IPCA (base year 2009).
(***) Significant at 1%, (**) significant at 5%, and (*) significant at 10%.

3.1.4 Rural vs. urban areas

Table 9 shows that the concentration of the population living in urban areas is high: 97.2% of Brazilians residents with a college degree live in urban areas.

The data in Table 10 show that the average hourly wage is significantly higher in urban areas. The average hourly wage for men is 54% higher than that of women in urban areas and 48% higher than that of women in rural areas. These wage gaps are statistically significant.

Table 9: Urban vs. rural areas for college degree holders, comparison between genders

Area	Total (%)	Men (%)	Women (%)
Urban	97.2	97.49	96.98
Rural	2.8	2.51	3.02
# Observations	40,895	17,015	23,880

Source: PNAD 2007, 2008, and 2009. Authors' tabulation.

Table 10: Hourly wage (in Brazilian reais, R$) according to urban or rural areas for college degree holders, comparison between genders.

Area	Total	Men	Women	Difference (%)
Urban	23.21 (51.21)	28.66 (55.08)	18.61 (47.21)	54.00 (***)
Rural	11.49 (19.06)	14.25 (25.10)	9.60 (13.10)	48.44 (***)
# Observations	40,895	17,015	23,880	

Source: PNAD 2007, 2008, and 2009. Authors' tabulation.
Wages were adjusted using the IPCA (base year 2009).
(***) Significant at 1%, (**) significant at 5%, and (*) significant at 10%.

3.1.5 Region of residence

Brazil is a large country and its population is very diverse. The distribution of college degree holders is shown in Table 11. As table 11 shows, there is a greater concentration of both men and women in the South and Southeast regions of the country. This fact reflects the higher education achievements among people living in the southern areas of the country as well in areas with higher economic development.

Table 11: Population distribution, comparison between genders.

Region	Total (%)	Men (%)	Women (%)
Midwest	12.78	12.56	12.94
Northeast	2.53	2.4	2.63
North	12.84	11.91	13.55
Southeast	43.42	44.6	42.53
South	28.43	28.53	28.35

Source: PNAD 2007, 2008, and 2009. Authors' tabulation.

Table 12 indicates that the Midwest, Southeast, and South provide higher wages for workers (R$25.96, R$24.06, and R$20.42, respectively). The Northeast provides the lowest wages (R$19.03). The demographic regions are important for explaining the wage gap between men and women with higher education. The salaries of men versus women, in order from the smallest to the largest wage gap, are as follows: Northeast (46.1%), Southeast (52.2%), South (52.6%), North (56.6%) and Midwest (64.7%).

Table 12: Hourly wage (in Brazilian reais, R$) and region of residence, comparison between genders.

Region	Total	Men	Women	Difference (%)
Midwest	25.96 (35.61)	33.12 (43.01)	20.11 (26.75)	64.69(***)
Northeast	19.03 (28.44)	23.26 (30.91)	15.92 (26.05)	46.11(***)
North	21.13 (69.94)	26.83 (41.86)	17.13 (76.87)	56.63(***)
Southeast	24.06 (54.77)	29.38 (64.75)	19.30 (43.40)	52.23(***)
South	20.42 (30.77)	25.11 (36.04)	16.45 (24.81)	52.64(***)
# Observations	53,346	24,080	29,266	

Source: PNAD 2007, 2008, and 2009. Authors' tabulation.
Wages were adjusted using the IPCA (base year 2009).
(***) Significant at 1%, (**) significant at 5%, and (*) significant at 10%.

3.2 Oaxaca decomposition

Previous section's results have sought to understand the effect of distinct characteristics on gender wage gap. However, it is the aggregated effect that results on the actual difference. Therefore, we perform Oaxaca decomposition to compare individuals with identical profiles and, with them, verify the existence of the gender gap in Brazil for individuals holding college degrees.

Two separate linear log wage regressions were calculated: one for women holding college degrees, and one for men with identical schooling. We controlled for age, experience, race, number of hours dedicated to housework, survey year, private or public sector, region of residence, occupational choice, and industry. We also used the square of individual age to account for the effect of inflation reducing real wages as individual workers grow older (see the appendices for more detailed regression results)). Given the absence of information about work experience in the database, we chose not to include the usual proxy for labor market experience – that is, a constructed variable using age minus years of schooling minus five years. We had several reasons for selecting this option. First, the constructed variable contains dubious assumptions about the immediate transition from school to work. Second, it assumes that years in school are not simultaneous to years in employment. Also, there is substantial amount of research questioning the lack of accuracy when using age minus years of schooling minus five years as a proxy for experience for female workers, given that they usually interrupt their labor market participation when they have children (see, for example, O'Neill and Polachek 1993; Nordman and Roubaud 2009).

The female sample regression indicated that the variables positively related to log wage were age, urban area, being of Asian descent, and residence at the Midwest region. The variables negatively related to log wage were experience; hours dedicated to housework; Black and Mixed races; and residence at the Northeast, North, or South regions. All variables were statistically significant with a 90% confidence level except indigenous race and employment in the public sector. The most significant variables were urban area, Black and Mixed races, and residence in the Midwest or Northeast regions.

The male sample regression showed that the variables positively related to log wage were age, residence in an urban area, and residence at the Midwest region. The variables negatively related to log wage were experience; hours dedicated to housework; Indigenous, Black, and Mixed races; and residence at the Northeast, North, or South regions. All variables were statistically significant with a 90% confidence level except being of Asian descent and employment in the public sector. The most significant variables were residence in an urban area, Black and Mixed races, and residence in the Midwest or Northeast regions.

A paired t-test was used to compare the significance of the difference in hourly wages between genders. The estimated male hourly wages were compared to the estimated female hourly wages in each regression, restricting the regression to females. Any differences found between incomes could then be attributed to discrimination, as the differences can only be explained by the individual's gender and not the wage-forming characteristics.

The results in Table 13 indicate a statistically significant difference in the wages of men and women holding college degrees, as demonstrated by the t-test. We initially found that the average income of men holding college degree was 54.37% higher than that of women (see Table 2). Table 13 shows that of the 54.37 percentage points of difference, 10.46% could be explained by the different characteristics of the male and female populations, and 43.91% could be attributed to unexplained reasons, which may include discrimination.

Table 13: The difference in hourly wages (in Brazilian reais, R$) according to gender by linear regression

	Men	Women	Difference (%)
Average hourly wage	18.19 (7.74)	12.64 (4.56)	43.91 (***) [154.38]
Number of observations	12,044		

Source: PNAD 2007, 2008, and 2009. Authors' tabulation.
Wages were adjusted using the IPCA (base year 2009).
(***) Significant at 1%, (**) significant at 5%, and (*) significant at 10%.
Between brackets, we show the t-statistic for the difference at the mean.

3.3 Quantile regression

The same procedure described above was used to test the hypothesis that the magnitude of discrimination differs along the income distribution curve. Instead of calculating the difference between the logarithms of the average hourly wages of men and women with higher education, we measured the discrepancy for five wage conditional quantiles: 10%, 25%, 50%, 75%, and 90%.

Table 14: The difference in hourly wages (in Brazilian reais, R$) according to gender using quantile regression

	Quantile 10%	Quantile 25%	Quantile 50%	Quantile 75%	Quantile 90%	OLS
Men	7.58 (3.36)	10.83 (4.70)	17.55 (7.67)	29.36 (13.31)	46.97 (21.10)	18.19 (7.74)
Women	5.54 (1.67)	8.02 (2.69)	12.05 (4.48)	19.28 (7.69)	30.53 (13.60)	12.62 (4.56)
Difference	36.82% (***) [105.05]	35.04% (***) [121.33]	45.64% (***) [150.11]	52.28% (***) [154.24]	53.85% (***) [148.50]	43.91% (***) [154.38]
# Observations	12,044	12,044	12,044	12,044	12,044	12,044

Source: PNAD 2007, 2008, and 2009. Authors' tabulation.
Wages were adjusted using the IPCA (base year 2009).
(***) Significant at 1%, (**) significant at 5%, and (*) significant at 10%.
Between brackets, we show the t-statistic for the difference at the mean.

The female sample regressions showed that the variables positively related to log wage were age and residence in urban area. The variables negatively related to log wage wee experience, hours dedicated to housework, Black and Mixed races, and residence at the North and South regions.

All variables were statistically significant at a 90% confidence level in all calculated quantile regressions, except by Indigenous race and being of Asian descent, employment in the public sector, and residence at the Midwest and Northeast regions. The most significant variables were residence in an urban area and Black race.

The male sample regressions for each quantile indicated that the variables positively related to log wage were age and urban area. The variables negatively related to log wage were experience, hours dedicated to housework, Black and Mixed races, and residence in the Northeast, North, and South. All variables were statistically significant at a 90% confidence level in all calculated quantile regressions except being of Asian descent and Indigenous race, employment in the public sector, and residence in the Midwest region. The most significant variables were residence in an urban area, Black and Mixed races, and residence in the Northeast.

The same paired test used in the Oaxaca decomposition described above was used to compare the average income between men and women. As income increases, the discrepancy in financial gains also increases. Table 14 shows that male income is 35.04% higher than that of females in the 25% quantile, whereas the difference is 53.85% in the 90% quantile.

4. Conclusion

The average wage gap between men and women in Brazil has recently been greatly reduced (Madalozzo 2010). However, a greater magnitude of disparities still can be observed between men and women holding college degrees. The present study aimed to assess the existence of discrimination in the income of women holding college degrees when compared to men in a similar situation. The linear and quantile regression methods were used to calculate women's disadvantages compared to men, taking into account their personal characteristics and current work assignments.

Based on the Oaxaca-Blinder decomposition and a linear regression approach, we divided the wage gap (54.37%) into two parts: one explained by both personal characteristics and work assignments (10.46 percentage points or 19.24% of the wage gap) and one not explained by these factors, which potentially represents discrimination (43.91 percentage points or 80.76% of the wage gap). Our results show that there is no equality of conditions in financial gains between men and women in the years 2007, 2008, and 2009 in Brazil. Occupational choices according to activity, work sector (whether public or private), and hours dedicated to housework explain a small portion of the inequality found. Characteristics such as age, experience, race, and demographic region also explain little of the observed discrepancy.

Following a quantile regression, we measured the gap along the income distribution curve and confirmed the results found with the linear regression approach: there is a notable difference between wages paid to men and women in Brazil in the reference period. We also observed an increase in wage difference as the financial gain increased. These latter results point to a deeper problem: when women achieve higher wages and, as a consequence, higher occupational positions, the gender wage gap is bigger than when they had lower wages with lower occupational positions.

In conclusion, these results represent an initial evidence for a "glass ceiling", an exclusively gender-based wage-gap-generating barrier found by Barros, Ramos, and Santos (1995). Even if women have identical labor supply conditions, they are paid less due to some form of barrier to the access to higher occupational positions, and this barrier leads to a bigger gender wage gap at the higher end of wage distribution, that is, in the higher quantiles. Testing the same hypothesis by assessing the progression throughout female participation in leadership positions has not yet been done. This means that there are possibilities for future studies that would add new information to this widely discussed topic. The results of such studies have great potential to

impact internal corporate policies and to enhance the role of women both in the labor market and in society.

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Appendices

Table A1: Linear regression for men with higher education

Log of hourly earnings	Coefficient	Standard Error	P-value
Constant	.7558345	.2938621	0.010
Age	.0674013	.0094125	0.000
Age Squared	-.0005466	.0001145	0.000
Hours spent on housework	-.0089716	.0017481	0.000
Year 2007 (D)	-.0032999	.022607	0.884
Year 2008 (D)	Omitted by collinearity		
Urban area (D)	.3417289	.0836551	0.000
Indigenous (D)	-.1600843	.153929	0.298
Black (D)	-.2394862	.053848	0.000
Asian descent (D)	-.0285414	.0946249	0.763
Mixed race (D)	-.1842779	.0283678	0.000
Public sector (D)	-.0301726	.0392513	0.442
Northeast (D)	-.1799727	.0419905	0.000
North (D)	-.1325891	.0343825	0.000
Midwest (D)	.1986054	.0328786	0.000
South (D)	-.100342	.0270529	0.000
Occupation (D)	Yes		
Activity (D)	Yes		
Number of Observations	5,540		
F (33, 5506)	57.19		
R-squared	0.1852		

Source: PNAD 2007, 2008, and 2009.

Notes:

i) Wages were adjusted using the IPCA based on the year 2009.

ii) D means dummy variables.

iii) Robust standard errors.

Table A2: Linear regression for women with higher education

Log of hourly earnings	Coefficient	Standard Error	P-value
Constant	.7816666	.1341476	0.000
Age	.0547957	.0048026	0.000
Age Squared	-.0004811	.0000587	0.000
Hours spent on housework	-.0085522	.0006369	0.000
Year 2007 (D)	.0290272	.0133708	0.017
Year 2008 (D)	Omitted by collinearity		
Urban area (D)	.2851547	.0297134	0.000
Indigenous (D)	.0620916	.1509006	0.637
Black (D)	-.1597511	.0333967	0.000
Asian descent (D)	.1730989	.0738717	0.001
Mixed race (D)	-.1532261	.0167915	0.000
Public sector (D)	-.0144	.0241187	0.492
Northeast (D)	-.1185563	.0225328	0.000
North (D)	-.2173325	.0185958	0.000
Midwest (D)	.0586703	.0207846	0.010
South (D)	-.1112051	.0175271	0.000
Occupation (D)	Yes		
Activity (D)	Yes		
Number of Observations	12,039		
F (33, 12005)	114.14		
R-squared	0.2436		

Source: PNAD 2007, 2008, and 2009.

Notes:

i) Wages were adjusted using the IPCA based on the year 2009.

ii) D means dummy variables.

iii) Robust standard errors.

Table A3: Quantile regression for men with higher education (10% quantile)

Log of hourly earnings	Coefficient	Standard Errors	P-value
Constant	.4028826	.2607146	0.122
Age	.0738688	.010474	0.000
Age Squared	-.0006684	.0001217	0.000
Hours spent on housework	-.0071129	.0021522	0.001
Year 2007 (D)	Omitted by collinearity		
Year 2008 (D)	.0289621	.0319757	0.365
Urban area (D)	.2906031	.1210459	0.016
Indigenous (D)	-.0674076	.1715027	0.694
Black (D)	-.2505376	.0803748	0.002
Asian descent (D)	.0822128	.1416197	0.562
Mixed race (D)	-.1611379	.0413974	0.000
Public sector (D)	.064263	.0537851	0.232
Northeast (D)	-.1426356	.0643427	0.027
North (D)	-.1937852	.0479962	0.000
Midwest (D)	.1115566	.0494571	0.024
South (D)	-.0172954	.0411475	0.674
Occupation (D)	Yes		
Activity (D)	Yes		
Number of Observations	5,540		
R-squared	0.1996		

Source: PNAD 2007, 2008, and 2009.

Notes:

i) Wages were adjusted using the IPCA based on the year 2009.

ii) D means dummy variables.

iii) Robust standard errors.

Table A4: Quantile regression for women with higher education (10% quantile)

Log of hourly earnings	Coefficient	Standard Errors	P-value
Constant	.8220669	.1563954	0.000
Age	.0413946	.0056645	0.000
Age Squared	-.000378	.000067	0.000
Hours spent on housework	-.0048575	.000747	0.000
Year 2007 (D)	Omitted by collinearity		
Year 2008 (D)	.0097936	.0166043	0.555
Urban area (D)	.1712521	.0490448	0.000
Indigenous (D)	.0682864	.1416101	0.630
Black (D)	-.1363503	.0410476	0.001
Asian descent (D)	.0265759	.0857611	0.757
Mixed race (D)	-.1761383	.0213035	0.000
Public sector (D)	.1171752	.0285825	0.000
Northeast (D)	-.0407654	.0314467	0.195
North (D)	-.1894504	.0235576	0.000
Midwest (D)	-.0078927	.0257337	0.759
South (D)	-.0619823	.0227265	0.006
Occupation (D)	Yes		
Activity (D)	Yes		
Number of Observations	12,039		
R-squared	0.1567		

Source: PNAD 2007, 2008, and 2009.

Notes:

i) Wages were adjusted using the IPCA based on the year 2009.

ii) D means dummy variables.

iii) Robust standard errors.

Table A5: Quantile regression for men with higher education (25% quantile)

Log of hourly earnings	Coefficient	Standard Errors	P-value
Constant	.8104574	.1861029	0.000
Age	.0662458	.0072343	0.000
Age Squared	-.0005648	.0000841	0.000
Hours spent on housework	-.0089304	.0015933	0.000
Year 2007 (D)	Omitted by collinearity		
Year 2008 (D)	-.0026903	.0227686	0.906
Urban area (D)	.2875872	.0850408	0.001
Indigenous (D)	-.1851093	.1988526	0.352
Black (D)	-.2261161	.054496	0.000
Asian descent (D)	.0360095	.096768	0.710
Mixed race (D)	-.1367331	.0296817	0.000
Public sector (D)	.1213873	.0384352	0.002
Northeast (D)	-.2205371	.0454868	0.000
North (D)	-.1950705	.0329101	0.000
Midwest (D)	.1277918	.0343624	0.000
South (D)	-.0695936	.0293322	0.018
Occupation (D)	Yes		
Activity (D)	Yes		
Number of Observations	5,540		
R-squared	0.1970		

Source: PNAD 2007, 2008, and 2009.
Notes:

i) Wages were adjusted using the IPCA based on the year 2009.
ii) D means dummy variables.
iii) Robust standard errors.

Table A6: Quantile regression for women with higher education (25% quantile)

Log of hourly earnings	Coefficient	Standard Errors	P-value
Constant	1.057676	.1596363	0.000
Age	.0467158	.0057596	0.000
Age Squared	-.0004073	.0000687	0.000
Hours spent on housework	-.0068607	.0007481	0.000
Year 2007 (D)	Omitted by collinearity		
Year 2008 (D)	-.0202947	.0165811	0.221
Urban area (D)	.1834048	.0468724	0.000
Indigenous (D)	-.1307108	.1439653	0.364
Black (D)	-.1623214	.041792	0.000
Asian descent (D)	.1060329	.0824629	0.199
Mixed race (D)	-.1692725	.020617	0.000
Public sector (D)	.0991221	.0283818	0.000
Northeast (D)	-.2416909	.0229363	0.029
North (D)	-.0022666	.0252071	0.000
Midwest (D)	-.1056523	.0224867	0.928
South (D)	-.1056523	.0224867	0.000
Occupation (D)	Yes		
Activity (D)	Yes		
Number of Observations	12,039		
R-squared	0.1540		

Source: PNAD 2007, 2008, and 2009.

Notes:

i) Wages were adjusted using the IPCA based on the year 2009.

ii) D means dummy variables.

iii) Robust standard errors.

Table A7: Quantile regression for men with higher education (50% quantile)

Log of hourly earnings	Coefficient	Standard Errors	P-value
Constant	1.402668	.1656496	0.000
Age	.0553656	.0064651	0.000
Age Squared	-.0004004	.0000757	0.000
Hours spent on housework	-.0098411	.0015238	0.000
Year 2007 (D)	Omitted by collinearity		
Year 2008 (D)	-.0191627	.0200759	0.340
Urban area (D)	.2546068	.0742311	0.001
Indigenous (D)	-.0657045	.1623053	0.686
Black (D)	-.1979439	.0472824	0.000
Asian descent (D)	-.039583	.0858783	0.645
Mixed race (D)	-.1607966	.0262291	0.000
Public sector (D)	.0179831	.0346069	0.603
Northeast (D)	-.1557462	.0395146	0.000
North (D)	-.1345241	.0286932	0.000
Midwest (D)	.1992245	.0295275	0.000
South (D)	-.1085917	.0256045	0.000
Occupation (D)	Yes		
Activity (D)	Yes		
Number of Observations	5,540		
R-squared	0.1848		

Source: PNAD 2007, 2008, and 2009.

Notes:

i) Wages were adjusted using the IPCA based on the year 2009.

ii) D means dummy variables.

iii) Robust standard errors.

Table A8: Quantile regression for women with higher education (50% quantile)

Log of hourly earnings	Coefficient	Standard Errors	P-value
Constant	1.415068	.1310967	0.000
Age	.0608897	.0047881	0.000
Age Squared	-.0005618	.0000577	0.000
Hours spent on housework	-.008381	.0006361	0.000
Year 2007 (D)	Omitted by collinearity		
Year 2008 (D)	-.0293889	.0136214	0.031
Urban area (D)	.2705443	.0384817	0.000
Indigenous (D)	.0985356	.1425186	0.489
Black (D)	-.1711165	.034249	0.000
Asian descent (D)	.0947332	.0686597	0.168
Mixed race (D)	-.1689532	.0166783	0.000
Public sector (D)	.0407585	.0234937	0.083
Northeast (D)	-.086005	.0242898	0.000
North (D)	-.2338223	.0185218	0.000
Midwest (D)	.0592622	.0201432	0.003
South (D)	-.1241239	.0183351	0.000
Occupation (D)	Yes		
Activity (D)	Yes		
Number of Observations	12,039		
R-squared	0.1429		

Source: PNAD 2007, 2008, and 2009.

Notes:

i) Wages were adjusted using the IPCA based on the year 2009.

ii) D means dummy variables.

iii) Robust standard errors.

Table A9: Quantile regression for men with higher education (75% quantile)

Log of hourly earnings	Coefficient	Standard Errors	P-value
Constant	1.263052	.2239897	0.000
Age	.0754072	.0087841	0.000
Age Squared	-.0006064	.0001037	0.000
Hours spent on housework	-.0085712	.0021647	0.000
Year 2007 (D)	Omitted by collinearity		
Year 2008 (D)	-.0133051	.0268049	0.620
Urban area (D)	.361359	.0972052	0.000
Indigenous (D)	-.0302083	.1892992	0.873
Black (D)	-.2428061	.0640657	0.000
Asian descent (D)	-.0717881	.1119164	0.521
Mixed race (D)	-.2264879	.0342789	0.000
Public sector (D)	-.0307073	.0468199	0.512
Northeast (D)	-.1472807	.0513475	0.004
North (D)	-.0661084	.0378339	0.081
Midwest (D)	.2708642	.0377358	0.000
South (D)	-.1198346	.0336509	0.000
Occupation (D)	Yes		
Activity (D)	Yes		
Number of Observations	5,540		
R-squared	0.1634		

Source: PNAD 2007, 2008, and 2009.

Notes:

i) Wages were adjusted using the IPCA based on the year 2009.

ii) D means dummy variables.

iii) Robust standard errors.

Table A10: Quantile regression for women with higher education (75% quantile)

Log of hourly earnings		Standard Errors	P-value
Constant	1.673571	.1875368	0.000
Age	.0626733	.0068262	0.000
Age Squared	-.0005434	.0000825	0.000
Hours spent on housework	-.009606	.0009779	0.000
Year 2007 (D)	Omitted by collinearity		
Year 2008 (D)	-.0167607	.0193891	0.387
Urban area (D)	.3435429	.0547407	0.000
Indigenous (D)	.1935947	.2192374	0.377
Black (D)	-.1087426	.0493492	0.028
Asian descent (D)	.2985257	.0973095	0.002
Mixed race (D)	-.1478615	.0234166	0.000
Public sector (D)	-.0308971	.0343342	0.368
Northeast (D)	-.1493536	.0339619	0.000
North (D)	-.2110263	.026038	0.000
Midwest (D)	.1123858	.0279104	0.000
South (D)	-.1172077	.0260098	0.000
Occupation (D)	Yes		
Activity (D)	Yes		
Number of Observations	12,039		
R-squared	0.1326		

Source: PNAD 2007, 2008, and 2009.

Notes:

i) Wages were adjusted using the IPCA based on the year 2009.

ii) D means dummy variables.

iii) Robust standard errors.

Table A11: Quantile regression for men with higher education (90% quantile)

Log of hourly earnings	Coefficient	Standard Errors	P-value
Constant	1.616384	.2707163	0.000
Age	.0858497	.0110691	0.000
Age Squared	-.0007027	.0001319	0.000
Hours spent on housework	-.0094848	.0027691	0.001
Year 2007 (D)	Omitted by collinearity		
Year 2008 (D)	.0297767	.0304557	0.328
Urban area (D)	.2690315	.1071401	0.012
Indigenous (D)	-.2310726	.199484	0.247
Black (D)	-.2772452	.0734415	0.000
Asian descent (D)	.1540138	.123297	0..212
Mixed race (D)	-.2252531	.0375708	0.000
Public sector (D)	-.1760633	.0557187	0.002
Northeast (D)	-.1691606	.0566745	0.003
North (D)	.0302484	.042641	0.478
Midwest (D)	.243001	.0409884	0.000
South (D)	-.1595698	.038081	0.000
Occupation (D)	Yes		
Activity (D)	Yes		
Number of Observations	5,540		
R-squared	0.1513		

Source: PNAD 2007, 2008, and 2009.
Notes:

i) Wages were adjusted using the IPCA based on the year 2009.
ii) D means dummy variables.
iii) Robust standard errors.

Table A12: Quantile regression for women with higher education (90% quantile)

Log of hourly earnings	Coefficient	Standard Errors	P-value
Constant	1.85688	.226182	0.000
Age	.0615213	.0085032	0.000
Age Squared	-.0005062	.0001048	0.000
Hours spent on housework	-.0104816	.00123	0.000
Year 2007 (D)	Omitted by collinearity		
Year 2008 (D)	-.0428687	.0232722	0.065
Urban area (D)	.4606053	.0619658	0.000
Indigenous (D)	.0657835	.2050839	0.748
Black (D)	-.2143881	.0580344	0.000
Asian descent (D)	.191269	.1212758	0.115
Mixed race (D)	-.1254193	.0277652	0.000
Public sector (D)	-.1455105	.0431788	0.001
Northeast (D)	-.2051877	.0396997	0.000
North (D)	-.1386125	.0311088	0.000
Midwest (D)	.1285991	.0329484	0.000
South (D)	-.1182948	.0311977	0.000
Occupation (D)	Yes		
Activity (D)	Yes		
Number of Observations	12,039		
R-squared	0.1327		

Source: PNAD 2007, 2008, and 2009.
Notes:

i) Wages were adjusted using the IPCA based on the year 2009.
ii) D means dummy variables.
iii) Robust standard errors.