Occupational and Income Polarization in the Labor Market: The Structure of Disadvantage by Gender and Race in Brazil

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Introduction

Over the last decades important changes have been observed in the Brazilian labor market, including changes in the myriad of occupations, either through extinction, loss of weight or appearance of new jobs, increase and decrease in demand for certain occupations, impacts of technology on occupations, increasing number of women entering the labor market, etc. This picture of changes has been based, among other factors, on the constant restructuring of firms in the labor market, through the impact of technological change in the required educational pattern of the labor force. This change, in turn, has generated an increased demand for workers with higher educational levels, required to carry out the tasks related to the occupation.

This article is in the line of research that seeks to determine such changes in the Brazilian labor market, from the analysis of occupational data in a comparison of wage returns attributed to the various occupational categories in the early 1980's to the 2000's. The analysis will be based on the use of data of Brazilian Household Sample Survey (PNAD) from 1987 to 2011, conducted by the Brazilian Census Bureau (IBGE). This database allows a representative historical overview of changes in occupations of the Brazilian labor market.

The impact of technology on the labor market can be understood as a process of replacement of human labor in routine tasks, manual or cognitive, but not in non-routine tasks (skilled and non-skilled occupations). The verification of this hypothesis implies that a technological impact would lead to an increased demand for skilled workers in jobs with high wages and for less-skilled workers with lower wages (i.e., occupations that require manual non-routine skills). It is expected then a "hollowing out" of intermediate occupations, which require routine manual skills. This process is called polarization of occupations.

This hypothesis should also be tested for median occupations, characterized by routine tasks. Since occupations are not evenly distributed along the wage distribution, routine occupations were concentrated in the middle of the distribution, non-routine occupations are concentrated in the lowest percentile, while the cognitive and interactive occupations occupy the highest percentiles. Likewise, technological progress leads to a drop in demand for medium jobs, resulting in an increase of the best jobs (that require less physical effort, superior education and management of advanced technologies) and of the worst (high physical exertion, low education and less technologized).

The polarization hypothesis is that an increasing demand for skills can be verified by changes in income and occupational structure. Thus, it is expected a shift in demand for occupations requiring less skill, using few technological resources and offer lower wages to occupations that require more specific skills, use more technology resources and remunerate better. The assessment of this hypothesis will be based on an occupational classification that assigns technological scores to the occupations according to their lesser or greater need for technological knowledge and management for the accomplishment of tasks. The development of a classification that uses this variable becomes necessary to capture changes in technology, automation in various sectors and creation of new jobs.

As an alternative procedure to the analysis by scores, the polarization is also verified under the hypothesis of increased demand for non-routine occupations, i.e. those for which the performance of its functions is not perfectly interchangeable with the existing technology. This initiative is intended to reflect the already consolidated results of polarization of the American workforce, the methodology that uses similar labels to identify the technological nature of a task in the Dictionary of Occupational Titles (DOT).

Moreover, given the scenario of increasing female participation in the labor force in recent decades, another crucial point is the measurement of gender wage inequality in recent decades in Brazil, from the perspective of this alternative approach. Racial inequality is equivalently relevant to be studied in this context, since the educational gap by race in Brazil is narrowing, but this is not translated to the patterns of participation and premiums in the labor market. The occupational segregation approach emphasizes the importance of location and occupational mobility in the process of realization of income. This approach highlights the disproportionate representation of women and non-whites in low status occupations, qualifications and income, with the implicit assumption that most of the wage gap could be overcome through an occupational progressive redistribution.

Therefore, this study aims to capture the increase in the demand for labor in sophisticated occupations under the hypothesis of technological progress and its effect on the earnings and allocation of women and non-white in occupations that require more management tools, technological processes and complex non-routine skills. Specific objectives are: (i) to assess the polarization of the Brazilian labor market from 1982 to 2011 under technological bias in favor of occupations that require more management tools and technological processes, and of non-substitutable occupations by existing technology, that require non-routine skills to their performance; (ii) to address the differential pays for the administration of complex technological resources and skills between men and women, non-white and white; and (iii) to explain the potential sources of income inequality in sophisticated occupational groups by mapping occupations in terms of differential wage gap by sex ratios, and wage gap by racial ratios over time.

Literature that investigates income inequality in the labor market demonstrates the persistence of the wage gap between men and women, non-white and white, emphasizing the global factors of the achievement of income, rather than factors specific to occupations or labor markets. These approaches provide useful insights about the factors that underlie gender inequalities. Nevertheless, an integrated perspective is needed on how the allocation in the labor market mediates the emergence of the gender and racial wage differential. Understanding how the location in the occupational structure determines the nature of the wage differential is essential to obtain a clearer view on the evolution of income inequality. If some positions in the labor market are associated with a more severe disadvantage of women and non-white, i.e., if there is an interaction between occupation, gender and race, to deal separately with these indicators overlooks a key element of stratification. Recently, the economic status of women is characterized by opposing tendencies: on the one hand, unprecedented numbers of women are in high-level professional, managerial and technical occupations. Occupational segregation declined greatly, allowing women into economic sectors previously dominated by men. The same trends could be observed for non-white men and women, in relation to their white counterparts, although in a lesser extent. Despite the gains by occupational segregation, women and non-white´s income remains lower than the income of their male and white colleagues in all economic levels, in spite of reducing the difference in education levels. Thus, the potential sources of income inequality at workplace are:

(i) **between occupations:** inequality is derived from a process of occupational classification where some occupations have higher wage rates than others. To the extent that women and non-white are disproportionately concentrated in low paid occupations, controlling for their individual attributes, the race and gender gap in earnings will inevitably emerge;

(ii) **within occupations:** men and women (non-white and white) in the same occupation have different wage rates. Some occupations present higher wage rates than others, leading to variation in gender (racial inequality) in income across the occupational structure;

(iii) **interaction between sources:** if the differential within occupations vary with average incomes between occupations, there is a relationship between average income and income inequality. Thus, the disadvantage of women and non-whites would increase as the average pay increase. However, with higher demand for skilled workers, high paid employees are increasingly hired, more based on their individual achievements than on their ascribed group characteristics.

The decomposition of the wage gap in these constituent parts allows checking the relative influence of individual vs. occupational effects and provides estimates of the sources of income inequality between vs. within occupations. In order to explain the mechanism operating in each occupational level, various occupational characteristics that may contribute to the observed pattern of inequality of income from each source are considered. Conventional models of least squares address the contribution of variables at the individual level to earnings inequality. A two-level hierarchical approach directly tests the persistence of the wage gap by gender and race according to occupational clusters. In this perspective, we attempt to demonstrate the effect of technological advancement on the pay of women and non-whites.

Data and Methods

The data source is the microdata from PNAD, IBGE for the years 1987 to 2011. The construction of databases and their analysis depended on the compatibility of occupational classifications. PNAD allows a study of characteristics and changes in the labor market, first, because it has a database of a few decades and, second, to always have in your research structure, one or more topics aimed to capture information from the Brazilian labor force. The concepts and classifications have changed over the period. Among the 1980, 1990 and 2000 changes occurred, trying to adapt the research standards used by the ILO. Moreover, during this period, there were changes in the existing range of occupations, with the appearance, weight loss or fusion of occupations previously considered distinct. This was also reflected on the relationship of occupations adopted by IBGE.

Subsequently, we performed the assignment of scores to technological occupations compatibilized created. This assignment followed the methodology adopted by Rodrigues, Hermeto and Albuquerque (2006), in which scores of technological variables were created based on concepts of Science and Technology and on keywords that relate in some way to technology. The technological variables were divided into three groups: technology stocks, technological labor resources and technology keywords. Individuals were aggregated into groups of education and technology. The technology groups emerged from the sum of the technological elements and boundaries of the strata was based on the simple division of the range of the scores for four strata (Extremely Low, Low, Medium, and High).

Besides the classification of occupations according to the scores of technology, another classification was performed according to the nature of the tasks necessary for its realization. This classification was based on Article Author, Levy and Murnane (2011) where occupations are classified into four distinct types: manual routine, routine cognitive, routine non-manual and non-routine cognitive. This segmentation is provided by belonging to American Dictionary of Occupational Titles (DOT), where:

Manual routine activities are defined as activities that require "the ability to move fingers and manipulate small objects rapidly and accurately";

Routine activities are activities that require cognitive "adaptability to situations requiring completion within certain limits, standards or tolerance";

Non-routine manual activities are activities that require "the ability to move the hand and foot coordinately with each other and in agreement with a visual stimulus," and

Non-routine cognitive activities are characterized by "adaptability to accept responsibility for the management, control and planning of an activity (...) may be related to education in general, Development and Mathematics."

Variables indicative of the requirements of an average American occupation, found in his dictionary of DOT titles were replicated and adapted to occupational groups. They were used as variables in second-level hierarchical models and will be explained in due course.

Basic Regressions for Labor Force Polarization

The first estimated equations of this article aim to test the hypothesis of technological bias and polarization. Trying to verify the hypothesis of an increasing demand for skills, we analyzed the changes in income and occupational structure over the period. The hypothesis is that there was a shift in favor of employment in occupations requiring education, management of processes and technological tools, which remunerate better, while the opposite should occur for the less complex occupations, with opposed characteristics. This shift in employment patterns can be interpreted as evidence of change in demand. The first OLS earnings equations have covariates of the technological level implied by the sum of elements in technology (dummies for the technology groups), besides years of schooling and dummies for sex and race.

Following the methodology of Autor, Levy and Murnane (2011) for the division of occupations according to the nature of their tasks and applying it to our compatible occupations, we reapply the econometric model in order to verify once more the demand for more skilled workers in face of technological progress over time. The hypothesis is that technology can replace human labor in routine, manual or non-manual, but not in non-routine tasks. The equation regresses the earnings return to schooling and dummies for sex, race and nature of the task (manual routine, routine non-manual, routine non-manual and non-routine non-manual).

Quantile Regressions for Labor Force Polarization

The purpose of using a quantile regression model here is to observe how different the impact of variables is across different quantiles of the distribution of wages. In this type of model, the regression is calculated for different percentiles, namely 10% poorer, poorest 50% or 50% richest and the richest 10% (according to the wage income). The hypothesis is that wage increases arising from non-routine non-manual occupations over time is greater for the highest quantile of the distribution, given the high correlation between wage and more sophisticated jobs, and therefore the highest correlation between the requirements and complexity of occupation is highlighted. Similarly to the OLS model, we estimate earnings equations by years of schooling and dummies for sex, race, technology groups and nature of the task. The quantiles of interest are the first q(0.1), referring to the poorest 10% of the population, the fifth q (0.5), to which is assigned equal weight to 50% lower and higher wages; and the tenth q(0.9), referring to the richest 10%.

Hierarchical Models

The analysis of levels *(multilevel analysis)* considers that the population is segmented according to several characteristics that are particular to certain groups. In this sense, the observations that fall into the same cluster tend to be more similar, i.e. have a higher correlation, which is expected to moderate as they move away toward the top of the chain. Advancing to the previous models, where the demand for more qualified labor was exclusively determined at the individual level, our interest is to understand how the skills necessary for the management of technological processes and other linguistic and logical functions are remunerated differently for man to women, non-whites and whites. Our objective is to decompose the source of the gender and racial wage gap under technological bias over time, i.e. how the various required skills are paid by gender and race, taking into account the increased demand for labor in occupations with greater requirements.

The hierarchical regression models *(multilevel regression models)* are essentially a version in levels of linear regression models. We estimate the two-levels regression model, which assumes that there is a set of hierarchical data with a single dependent variable measured at the lowest level, and independent variables at all levels. The models proposed in this section includes individuals at the basic level, and occupations as the second level and earnings as the dependent variable, in specific estimates by race, gender and period. The method allows that second level observations have different random intercept and elasticity coefficients. The ANOVA model with random effects is important because it allows to decompose the variance into two separate components, namely, σ^2 representing the variance at the individual level, and τ_{00}, the variance at the occupational level. They allow the computation of the coefficient of correlation (ρ), which indicates the proportion of the variability of the wages between the second level and the total sample, i.e., how variation of the whole model is due to between-occupations wage variation.

With the aim of deepening the analysis of the reduction of the wage gap between men and women over time, we estimate for each year of analysis, hierarchical models controlled for sex and race of individuals. At the individual level, it is estimated the logarithm of deflated earnings as a function of individual human capital, age and an error with random distribution. The second level reflects the sensitivity of the parameters that characterize a group of occupation to remunerate men and women, non-whites and whites differently, in order to investigate the increase in the remuneration of women and non-whites in more sophisticated occupations. The technological and educational requirements necessary for the performance of the work required in these occupations specifies the second level. Two variables are dummies for technology groups that can be exchanged for dummies related to the nature of the task; FF ranges from 1 to 4 according to the amount of physical effort required for performance of the task, REGR, REGM and REGL range from 1 to 6 indicating, respectively, grammatical requirements, mathematical and logical; AES indicates the minimum education accepted by employers for full performance of work; AEX expresses the average experience of workers required in number of years.

Explanation of potential sources of income inequality in sophisticated occupational groups

Once captured the different sensitivities to the pay of the qualifications required over time for men and women, non-whites and whites, our final objective is to identify the most sophisticated occupations classified which, classified in high technological and / or non-routine non-manual strata, tend to compensate and absorb more or less labor according to gender and race. The procedure should explain the potential sources of income inequality in the most sophisticated occupational groups – whether it is derived from the disparity of sex and racial ratios or to different wages within the occupation.

We compute the differential of the wage gap between men and women (non-whites and whites), in the occupations of the groups in analysis and the differential of the sex (race) ratio within occupations between the years. The occupations are plotted in a 2x2 matrix, where the y-axis represents the difference of the sex ratio and the x-axis represents the differential of the wage gap. Illustrating the point for the gender perspective, the quadrants formed state:

• Negative differential wage gap and positive sex ratio (upper left): women in 2011 earn more relative to men than in 1987, in face of increasing proportion of men in the occupation. The quadrant is representative of the intensification of the source of income inequality between occupations, but also the weakening of the source of inequality within occupations.

• Negative differential wage gap and negative sex ratio (lower left): women in 2011 earn more relative to men than in 1987, in face of increasing proportion of women in the occupation. The quadrant confirms the weakness of the sources of inequality between and within occupations.

• Positive differential wage gap and positive sex ratio (upper right): women in 2011 earn less relative to men than in 1987, in face of increasing proportion of men in the occupation. The quadrant is indicative of our persistence of wage inequality between and within occupations.

• Positive differential wage gap and negative sex ratio (lower right): women in 2011 earn less relative to men than in 1987, in face of increasing proportion of women. The quadrant determines the combination of the weakening of the sources of inequality between occupations and the strengthening of inequality within occupations.

Results

Basic statistics and regressions for polarization of the workforce

Trying to verify the hypothesis of an increasing demand for skills, we analyzed the changes in income and occupational structure for the years 1987 and 2011. Throughout the period, the hypothesis is that there was a shift in employment in occupations requiring less education and offer lower wages for occupations requiring more education, management processes and technological tools and remunerate better. This shift in employment patterns can be interpreted as evidence of a shift change in demand in more complex occupations. The first procedure in order to test this hypothesis was the crossing of the deciles of the wage distribution and the average sum of the technological elements (scores assigned to each occupation). We verified the increase in intensity of the correlation between wages and technological tools and processes (Table 1). Moreover, the increase in 2011 of the mean scores of technology signals an increased use of technology resources throughout the wage distribution.

Table 1: Technology Scores of Occupations by wage distribution deciles, Brazil, 1987-2011 (%)

Deciles	1987	2011
1	5.09	5.57
2	5.73	5.92
3	6.25	6.60
4	7.16	7.19
5	7.69	7.85
6	8.33	8.47
7	9.07	9.23
8	10.43	10.53
9	11.64	12.06
10	14.23	14.68

Source: Brazilian Household Sample Surveys Microdata, 1987, 2011.

The increased demand for employment in positions that require more skills and operational technology should respond by increasing the level of income of these occupations over time. For all categories and years, male and whites wages are higher than female and non-whites wages and the proportional difference between them remains by strata. The gender gap, however, is reduced over time in all segments, standing out the actual increase in high technological stratum for women (Tables 2 and 3). In subsequent regressions, when the variance of wages is no longer explained only by the technological level, the results demonstrate the reasonableness of the hypothesis of polarization.

Table 2: Average wages by occupational technological category, gender and race, Brazil, 1987-2011

	1987				2011			
Technological Category	Non-white women	White Women	Non-white men	White men	Non-white women	White Women	Non-white men	White men
Extremely Low	448.4	565.8	934.0	1274.2	584.6	731.8	871.9	1191.8
Low	634.6	1120.4	1382.6	2041.8	839.8	1157.5	1141.3	1585.7
Intermediate	1469.8	1984.7	1942.0	2953.7	1379.6	1917.1	1707.6	2326.1
High	2443.5	3226.4	3375.8	5578.3	2032.8	2979.3	2884.9	4544.2
Total	752.2	1411.5	1491.9	2751.0	906.6	1483.3	1340.1	2186.8

Source: Brazilian Household Sample Surveys Microdata, 1987, 2011.

Table 3: Average wages, by nature of tasks, gender and race, Brazil, 1987-2011

	1987				2011			
Nature of tasks	Non-white women	White women	Non-white men	White men	Non-white women	White women	Non-white men	White men
Routine manual	421.4	533.3	1048.1	1358.3	595.4	731.4	1002.8	1230.2
Non-routine manual	509.1	696.0	1215.2	1695.4	646.0	833.3	1055.5	1373.2
Routine non-manual	1060.5	1578.3	1677.0	2416.9	919.2	1240.1	1316.3	1761.2
Non-routine non-manual	1778.1	2525.7	3456.7	5306.4	1827.6	2604.9	2893.1	4268.8
Total	752.2	1411.5	1491.9	2751.0	906.6	1483.3	1340.1	2186.8

As a model for measuring the tendency of divergence of average wages between individuals in occupations with different levels of technology, we estimated wage regressions by years of schooling, dummies for technology categories and nature of tasks of the occupations, separately for the gender and race groups via OLS. For all groups, the regressions yielded increasing coefficients for the categories other than the extremely low technology category. Over time the relative coefficients of the low and intermediate categories lose significance. The same can not be said about the coefficient on the dummy's upper stratum of technology. The coefficient is positive and gains in scale over the years for women, and it remains large for men. The results show a higher propensity of individuals in the most technologically advanced occupations to hold higher wages, with positive bias over time mostly for women.

The variation of the relative proportion of the technological group and technical-educational groups in the sample confirms this result. There was a positive variation of the groups that use more technology and have more years of study and the opposite occurring for the lower technology group. Interestingly, the flow of white women into more sophisticated occupations over time, almost reaching white men for the analysis of the technology groups, is shown in table 4. Based on this fact, we will test whether the increase in demand for more qualified to an occupation that requires more technological skills and the admission of more women into this category meant that the wage gap in occupations most sophisticated to be reduced more than proportionally than the decrease of the average gap between men and women over time.

Table 4: Labor force distribution by occupational technological category, gender and race, Brazil, 1987-2011

	1987					2011				
Technological Category of Occupation	Non-white women	White women	Non-white men	White men	Total	Non-white women	White women	Non-white men	White men	Total

Extremely Low	38.4	23.2	25.8	15.0	22.7	38.4	23.9	23.7	15.2	24.4
Low	42.1	40.0	48.7	44.1	43.9	36.3	35.8	49.1	44.4	41.9
Intermediate	16.8	28.9	19.0	23.5	22.8	18.8	26.3	19.5	23.2	22.1
High	2.7	7.9	6.5	17.3	10.6	6.5	13.9	7.7	17.3	11.6
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Source: Brazilian Household Sample Surveys Microdata, 1987, 2011.

Following the methodology of Autor, Levy and Murnane (2011) for the division of occupations according to the nature of the task and applying it to the Brazilian occupations, in order to reinforce the demand for more skilled workers in the face of technological progress over time. The hypothesis is that technology can replace human labor in routine, manual or non-manual, but not in non-routine tasks. The stratum that is used as reference is constituted by non-routine manual tasks. It is expected that, over the years, the median wages returns of occupations, namely, routine manual and routine non-manual, to fall and those of the non-routine are expected to rise. The estimation shown in tables 5 and 6, in this sense, confirms the trend. The coefficients on the dummies for routine non-manual and non-routine manual occupations fall significantly. Still, according to the model the non-routine non-manual occupations are better paid.

Table 5: OLS Coefficients of the Log-Wage Regression, by Gender and Race, Brazil, 1987

Explanatory Variables	Non-white women (1)	Non-white women (2)	White women (1)	White women (2)	Non-white men (1)	Non-white men (2)	White men (1)	White men (2)
Years of schooling	0.1325*** (0.0124)	0.0971 *** (0.0104)	0.1404 *** (0.0087)	0.0977 *** (0.0082)	0.1067 *** (0.0066)	0.0817 *** (0.0051)	0.1244 *** (0.0072)	0.0919 *** (0.0032)
Age	0.0655 *** (0.0087)	0.0652 *** (0.0103)	0.0775 *** (0.0091)	0.0812 *** (0.0073)	0.1065 *** (0.0081)	0.0986 *** (0.0084)	0.1376 *** (0.0069)	0.1224 *** (0.0014)
Age squared	-0.0007*** (0.0001)	-0.0007 *** (0.0001)	-0.0008*** (0.0001)	-0.0009 *** (0.0001)	-0.0012*** (0.0001)	-0.0011 *** (0.0001)	-0.0015*** (0.0001)	-0.0014 *** (0.0001)
Tech. Categ.								
Low		-0.3039 (0.2400)		-0.0929 (0.2444)		0.1733 (0.1064)		0.1881 * (0.1068)
Intermediate		-0.1615 (0.2438)		-0.0441 (0.2465)		0.2634 ** (0.1153)		0.2168 * (0.1129)
High		0.2814 (0.2936)		0.3905 (0.2609)		0.4375 *** (0.1214)		0.4845 *** (0.1115)
Nat. Tasks								
Non-routine manual		0.1764 (0.2512)		0.2096 (0.2520)		-0.0202 (0.0968)		0.0463 (0.0966)
Routine non-manual		0.5691 ** (0.2341)		0.5334 ** (0.2366)		0.0180 (0.0814)		0.0434 (0.0905)
Non-routine non-manual		0.5344 * (0.2798)		0.5907 ** (0.2616)		0.3403 *** (0.0926)		0.3684 *** (0.3684)
Constant	4.0533 *** (0.1905)	4.1821 *** (0.2266)	3.9764 *** (0.2038)	3.9458*** (0.1405)	4.2311 *** (0.1625)	4.3416 *** (0.1975)	3.6655 *** (0.1590)	3.9266 *** (0.1522)
R^2	0.3108	0.3548	0.4026	0.4492	0.2533	0.2913	0.3769	0.4366
N	8767		11815		13598		19364	

Source: Brazilian Household Sample Surveys Microdata, 1987.
Obs.: Standard errors in brackets.
Obs.: level of significance: * 10%; ** 5%; *** 1%.

Table 6: OLS Coefficients of the Log-Wage Regression, by Gender and Race, Brazil, 2011

Explanatory Variables	Non-white women (1)	Non-white women (2)	White women (1)	White women (2)	Non-white men (1)	Non-white men (2)	White men (1)	White men (2)
Years of schooling	0.0915*** (0.0074)	0.0589 *** (0.0071)	0.1172 *** (0.0079)	0.0718 *** (0.0092)	0.0735 *** (0.0071)	0.0534 *** (0.0043)	0.1020 *** (0.0103)	0.0667 *** (0.0062)
Age	0.0283 ***	0.0275 ***	0.0506 ***	0.0486 ***	0.0582 ***	0.0512 ***	0.0662 ***	0.0586 ***

	(0.0071)	(0.0049)	(0.0101)	(0.0064)	(0.0066)	(0.0039)	(0.0091)	(0.0067)
	-0.0002***	-0.0002 ***	-0.0005***	-0.0005 ***	-0.0005***	-0.0005 ***	-0.0006***	-0.0005 ***
Age squared	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0001)
Tech. Categ.								
		0.1072		0.0923		0.0352		0.0539
Low		(0.0707)		(0.0644)		(0.0698)		(0.0725)
		0.2914***		0.2054 **		0.1854 **		0.1504 *
Intermediate		(0.1043)		(0.0983)		(0.0749)		(0.0770)
		0.5177***		0.5142 ***		0.3519 ***		0.4182 ***
High		(0.1337)		(0.1114)		(0.0948)		(0.0965)
Nat. Tasks								
Non-routine		-0.0592		-0.0073		-0.0335		0.0157
Manual		(0.0755)		(0.0574)		(0.0616)		(0.0640)
Routine		0.0287		0.1075		-0.0307		0.0224
Non-manual		(0.0941)		(0.0655)		(0.0572)		(0.0586)
Non-routine		0.3397 ***		0.4261 ***		0.3317 ***		0.4223 ***
Non-manual		(0.1064)		(0.1041)		(0.0733)		(0.0858)
	4.0533 ***	4.1821 ***	4.4506 ***	4.6742***	4.9252 ***	5.1410 ***	4.6537 ***	4.9504 ***
Constant	(0.1905)	(0.2266)	(0.2254)	(0.1405)	(0.1738)	(0.1266)	(0.2566)	(0.1522)
R^2	0.2325	0.3050	0.2936	0.3867	0.2066	0.2626	0.2850	0.3846
N	21484		21539		28818		24881	

Source: Brazilian Household Sample Surveys Microdata,, 2011.
Obs.: Standard errors in brackets.
Obs.: level of significance: * 10%; ** 5%; *** 1%.

Quantile Regressions

Since the upper deciles of the Brazilian wage distribution are related to higher average sum of scores of technology in both years, the purpose of using a quantile regression model here is to observe how the impact of variables across different quantiles of the distribution of wages varies. In this type of model, the regression is calculated for different percentiles, namely 10% poorer and the richest 10% (according to the wage income). The hypothesis is that wage´s increases arising from non-routine non-manual occupations over time is greater for the highest quantile of the distribution, given the high correlation between wage and greater sophistication of the occupations. As in the OLS model, the wage return was regressed on years of schooling, age, and dummies for technological categories and nature of tasks of the occupations. The quantiles of interest were the first (0.1), referring to the poorest 10% of the population and the tenth (0.9), referring to the richest 10%. We found an increasing polarization of income for the top decile of the wage distribution in Brazil, as tables 7 and 8 show. With greater weight given to observations concentrated in the richest 10%, the high correlation between more sophisticated occupations and higher wages highlights the shift in the demand for professionals capable of performing non-routine tasks. The returns to years of schooling are higher for the upper quantiles, but decreasing over time in all examined quantiles.

Table 7: Quantile Regression Coefficients, by Gender and Race, Brazil, 1987

Explanatory	Non-white women		White women		Non-white men		White men	
Variables	0,10	0,90	0,10	0,90	0,10	0,90	0,10	0,90
Years of	0.1111 ***	0.0874 ***	0.0931 ***	0.0955 ***	0.0659 ***	0.0855 ***	0.0803 ***	0.0957 ***
schooling	(0.0060)	(0.0055)	(0.0048)	(0.0049)	(0.0030)	(0.0041)	(0.0027)	(0.0031)
	0.0680 ***	0.0832 ***	0.0955 ***	0.0755 ***	0.0722 ***	0.1049 ***	0.1159 ***	0.1016 ***
Age	(0.0155)	(0.0170)	(0.0137)	(0.0130)	(0.0092)	(0.0127)	(0.0089)	(0.0100)
	-0.0007 ***	-0.0009 ***	-0.0011 ***	-0.0007 ***	-0.0008 ***	-0.0011 ***	-0.0014 ***	-0.0011 ***
Age squared	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
Tech. Categ.								

Low	-0.5034*** (0.0498)	-0.0559 (0.0490)	-0.4081*** (0.0596)	0.1616 *** (0.0496)	0.1176 *** (0.0250)	0.1918 *** (0.0334)	0.1997 *** (0.0318)	0.1317 *** (0.0321)
Intermediate	-0.2215*** (0.0805)	-0.0716 (0.0802)	-0.1949*** (0.0726)	0.0748 (0.0656)	0.2499 *** (0.0341)	0.2253 *** (0.0495)	0.3295 *** (0.0391)	0.1026 ** (0.0403)
High	0.0776 (0.1216)	0.5671 *** (0.1081)	0.1416 (0.0883)	0.5370 *** (0.0734)	0.3759 *** (0.0520)	0.3772 *** (0.0689)	0.6081 *** (0.0461)	0.3097 *** (0.0470)
Nat. Tasks								
Non-routine manual	-0.0420 (0.0638)	0.0974 (0.0625)	0.4127 *** (0.0646)	0.0341 (0.0571)	-0.0963*** (0.0255)	0.0411 (0.0343)	-0.0216 (0.0310)	0.1234 *** (0.0312)
Routine non-manual	0.6639 *** (0.0600)	0.5809 *** (0.0561)	0.7504 *** (0.0628)	0.4727 *** (0.0551)	-0.0864 *** (0.0278)	0.1867 *** (0.0380)	-0.0978 *** (0.0317)	0.2076 *** (0.0325)
Non-routine non-manual	0.4731 *** (0.0933)	0.6465 *** (0.0843)	0.7966 *** (0.0771)	0.5392 *** (0.0692)	0.2320 *** (0.0450)	0.5678 *** (0.0563)	0.2495 *** (0.0404)	0.5342 *** (0.0410)
Constant	3.1677 *** (0.3008)	4.6925 *** (0.3271)	2.8232 *** (0.2662)	4.7884 *** (0.2516)	4.2758 *** (0.1775)	4.8911 *** (0.2444)	3.4071 *** (0.1522)	5.0207 *** (0.1940)
Pseudo R^2	0.1873	0.2805	0.2348	0.2881	0.0908	0.2211	0.1895	0.2976

Source: Brazilian Household Sample Surveys Microdata, 1987.
Obs.: Standard errors in brackets.
Obs.: level of significance: * 10%; ** 5%; *** 1%.

Table 8: Quantile Regression Coefficients, by Gender and Race, Brazil, 2011

Explanatory	Non-white women		White women		Non-white men		White men	
Variables	0,10	0,90	0,10	0,90	0,10	0,90	0,10	0,90
Years of schooling	0.0818 *** (0.0026)	0.0544 *** (0.0027)	0.0759 *** (0.0028)	0.0834 *** (0.0036)	0.0401 *** (0.0011)	0.0600 *** (0.0022)	0.0494 *** (0.0017)	0.0698 *** (0.0028)
Age	0.0256 *** (0.0082)	0.0410 *** (0.0077)	0.0402 *** (0.0085)	0.0631 *** (0.0082)	0.0195 *** (0.0034)	0.0749 *** (0.0071)	0.0440 *** (0.0052)	0.0703 *** (0.0079)
Age squared	-0.0003 *** (0.0001)	-0.0003 *** (0.0001)	-0.0004 *** (0.0001)	-0.0006 *** (0.0001)	-0.0002 *** (0.0000)	-0.0007 *** (0.0001)	-0.0004 *** (0.0001)	-0.0006 *** (0.0001)
Tech. Categ.								
Low	0.2642*** (0.0246)	0.1150 *** (0.0275)	0.2843*** (0.0028)	0.0493 (0.0343)	0.0218 ** (0.0099)	0.0238 (0.0196)	0.0453 ** (0.0185)	0.0191 (0.0261)
Intermediate	0.6816*** (0.0330)	0.1684 *** (0.0366)	0.4376*** (0.0345)	0.0729 * (0.0418)	0.1535 *** (0.0133)	0.1700 *** (0.0272)	0.1516 *** (0.0231)	0.0802 ** (0.0326)
High	0.7398*** (0.0447)	0.5684 *** (0.0366)	0.6079*** (0.0413)	0.4933 *** (0.0449)	0.2692 *** (0.0210)	0.3970 *** (0.0374)	0.3602 *** (0.0286)	0.3252 *** (0.0382)
Nat. Tasks								
Non-routine manual	-0.2294*** (0.0308)	-0.0532 (0.0326)	-0.1985*** (0.0340)	0.0712 * (0.0409)	-0.0564*** (0.0099)	-0.0167 (0.0194)	-0.0282 (0.0177)	0.0530 ** (0.0254)
Routine non-manual	-0.1241 *** (0.0283)	0.1875 *** (0.0308)	-0.0660** (0.0306)	0.2511 *** (0.0360)	-0.0966 *** (0.0114)	0.0947 *** (0.0223)	-0.0647 *** (0.0192)	0.1172 *** (0.0265)
Non-routine non-manual	-0.0507 (0.0366)	0.6779 *** (0.0365)	0.0971 *** (0.0376)	0.6777 *** (0.0409)	0.0873 *** (0.0181)	0.5804 *** (0.0304)	0.1933 *** (0.0255)	0.7241 *** (0.0317)
Constant	4.2146 *** (0.1630)	4.6925 *** (0.3271)	4.2399 *** (0.1703)	4.8465 *** (0.2516)	5.4527 *** (0.1775)	4.8911 *** (0.2444)	4.9300 *** (0.1056)	5.3398 *** (0.1940)
Pseudo R^2	0.1682	0.2669	0.1621	0.2801	0.0510	0.2180	0.1106	0.2935

Source: Brazilian Household Sample Surveys Microdata, 2011.
Obs.: Standard errors in brackets.
Obs.: level of significance: * 10%; ** 5%; *** 1%.

Hierarchical Models

To test the impact of technological advances on the allocation and remuneration of women and non-whites, we used hierarchical models. Since it evidenced the reduction of the gender wage gap, we aim now to prove the reduction of the same gap in wage returns of occupations that require more skills and employ more technological resources. To do so, we estimated exclusive equations for men and women. Then the procedure is reapplied for non-whites and whites.

The ANOVA model with random effects, shown in table 9, attests the reduction of the wage gap between men and women between 1987 and 2011. The intra-class correlation coefficients provide the first indication that the remuneration of women against men is more susceptible to occupational characteristics. One may speculate that the bonus pay awarded to men varies across a wider range despite the occupational characteristics. The positive coefficient of 1987 to 2011 indicates that the demand is greater to more specific skills, compatible to the professional performance of tasks required by the occupation. The requirement for the employment of women remains higher than that which applies to men, although it has decreased proportionally.

Table 9: ANOVA Results, by Gender and Race, Brazil, 1987-2011

Explanatory Variables	Non-white women		White women		Non-white men		White men	
	1987	2011	1987	2011	1987	2011	1987	2011
Constant	6.1247 *** (0.0091)	6.5102 *** (0.0051)	6.9957 *** (0.0101)	6.8395 *** (0.0047)	7.1613 *** (0.0096)	6.9025 *** (0.0040)	7.5355 *** (0.0076)	7.2975 *** (0.0050)
Variance Partition								
Individual Level	0.6244	0.4326	0.6068	0.4346	0.5129	0.3611	0.5650	0.4356
Occupational Level	0.3044	0.2582	0.1835	0.1757	0.1991	0.0845	0.1850	0.1516
Intra-Class Correlation	0,3277	0,3738	0,2322	0,2879	0,2796	0,1896	0,2467	0,2582

Source: Brazilian Household Sample Surveys Microdata, 1987, 2011.
Obs.: Standard errors in brackets.
Obs.: level of significance: * 10%; ** 5%; *** 1%.

Table 13 shows the main model, which specifies the second-level occupational variables in order to reflect the sensitivity of the parameters that characterize a group of occupation to remunerate men and women differently, taking into account the higher correlation between members of the same occupation. The estimation sustains the hypothesis of reduction of the wage gap to management of technological resources between men and women over time. The effect of polarization with technological bias is signifcant on the remuneration of the use of advanced technological resources for women, and the gender difference reduces. The returns associated with non-manual non-routine activities converge for white men and women over time, but not for non-white women, for whom it raises significantly, reducing additionally the gap. The impact of occupational polarization under technological bias in this perspective is to reduce the gap in wage returns of occupations with more complex requirements, proving the previous hypothesis. It is worth noting that, at the individual level, the reduction of the wage gap between men and women is fostered by the reduction of the difference between the wages by years of schooling and age. We can conclude that the impact of polarization with technological bias in the fall of the gender gap over time is due to the requirements of complex occupations and to the use of technological resources.

Table 13: Hierarchical models coefficients, by Gender and Race, Brazil, 1987-2011

Explanatory Variables	Non-white women		White women		Non-white men		White men	
	1987	2011	1987	2011	1987	2011	1987	2011
Years of schooling	0.0879 *** (0.0029)	0.0490 *** (0.0013)	0.0938 *** (0.0024)	0.0619 *** (0.0014)	0.0851 *** (0.0019)	0.0505 *** (0.0009)	0.0929 *** (0.0015)	0.0619 *** (0.0012)
Age	0.0721 *** (0.0080)	0.0294 *** (0.0042)	0.0870 *** (0.0065)	0.0480 *** (0.0042)	0.0912 *** (0.0056)	0.0464 *** (0.0033)	0.1144 *** (0.0048)	0.0554 *** (0.0037)
Age squared	-0.0008*** (0.0001)	-0.0003*** (0.0001)	-0.0010*** (0.0001)	-0.0005*** (0.0001)	-0.0010*** (0.0001)	-0.0004*** (0.0000)	-0.0013*** (0.0001)	-0.0005*** (0.0000)

Tech. Categ.								
	0.2648 ***	0.0764 ***	0.2458 ***	0.1652 ***	-0.0480***	0.0117	-0.0145	0.0702 ***
Low	(0.0349)	(0.0168)	(0.0366)	(0.0231)	(0.0194)	(0.0104)	(0.0213)	(0.0147)
	0.3901 ***	0.2088 ***	0.3464 ***	0.4234 ***	0.0611 ***	0.1332 ***	0.0603 ***	0.1168 ***
Intermediate	(0.0507)	(0.0228)	(0.0448)	(0.0275)	(0.0205)	(0.0149)	(0.0253)	(0.0253)
	0.4846 ***	0.5796 ***	0.2403 ***	0.6585 ***	-0.0298	0.0957***	0.0796 ***	0.2283***
High	(0.0708)	(0.0238)	(0.0512)	(0.0293)	(0.0461)	(0.0257)	(0.0330)	(0.0220)
Nature of Tasks								
Non-routine	-0.5834***	0.0539***	0.1304***	0.0702***	-0.1295***	0.1547***	0.1531***	-0.0280***
manual	(0.0456)	(0.0203)	(0.0352)	(0.0255)	(0.0187)	(0.0111)	(0.0184)	(0.0132)
Routine	0.1093 ***	0.5965 ***	0.2854 ***	0.1401 ***	-0.0791***	-0.1322***	0.1717 ***	-0.0645***
non-manual	(0.0383)	(0.0238)	(0.0362)	(0.0241)	(0.0206)	(0.0123)	(0.0198)	(0.0143)
Non-routine	0.1195 ***	0.7653 ***	0.7231 ***	0.2327 ***	0.3859 ***	0.1390 ***	0.4315 ***	0.0713 ***
non-manual	(0.0522)	(0.0251)	(0.0423)	(0.0275)	(0.0334)	(0.0218)	(0.0248)	(0.0206)
	4.1819 ***	4.8705 ***	3.6186 ***	4.7674 ***	4.4716 ***	5.4533 ***	4.0201 ***	5.2559 ***
Constant	(0.1556)	(0.0839)	(0.1556)	(0.0847)	(0.1097)	(0.0655)	(0.0944)	(0.0764)
Variance Partition								
Individual Level	0.5566	0.3867	0.5279	0.3933	0.4406	0.3445	0.4633	0.3783
Occupational Level	0.0631	0.0537	0.0644	0.0779	0.0468	0.0411	0.0693	0.0574
Intra-Class Correlation	0,1018	0,1219	0,1087	0,1653	0,0960	0,1066	0,1301	0,1317

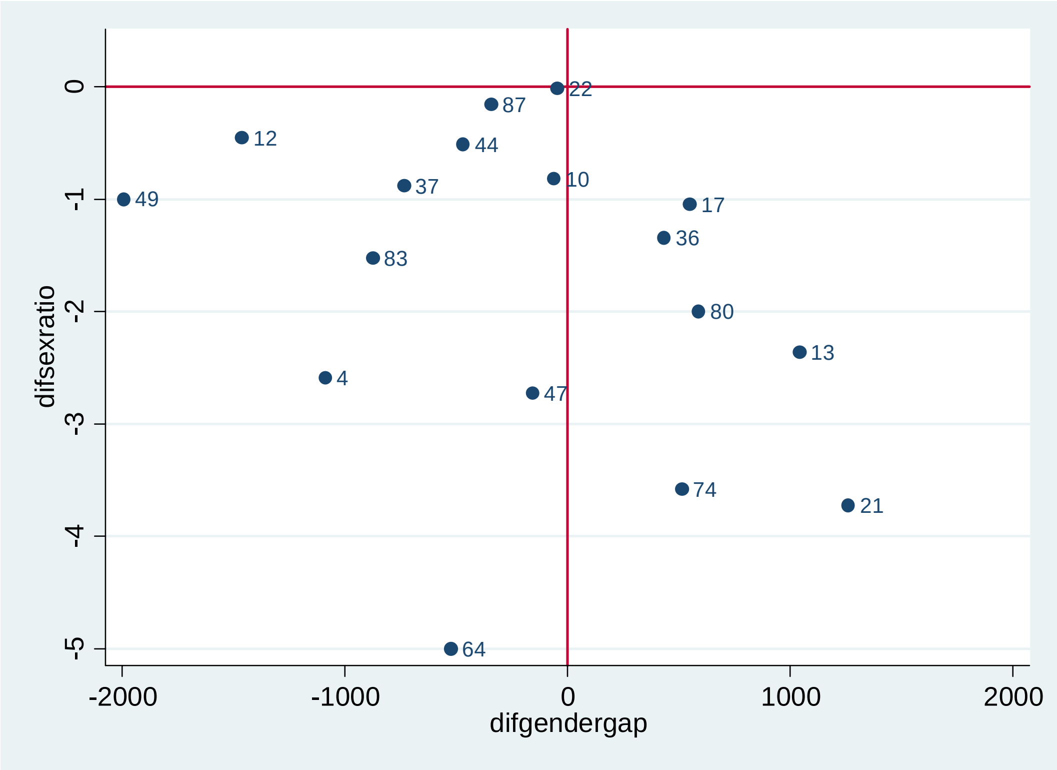
Source: Brazilian Household Sample Surveys Microdata, 1987, 2011.
Obs.: Standard errors in brackets.
Obs.: level of significance: * 10%; ** 5%; *** 1%.

Comparison: allocation and differential pay for advanced technology groups

In order to identify the distribution of sources of wage inequality in the groups where there was an increase in demand for professionals given the technological bias, we map occupations in high and low technological categories, and their placement in a 2x2 matrix, indicative of the differential wage gap and sex ratio over time. As it was shown by hierarchical models for remuneration of technological attributes required in an occupation, the top technological category rewarded fewer women from 1987 to 2011 regarding the use of technology. The graphical analysis deepens the analysis of the sources of wage inequality and occupations in which they influence. For instance, Figure 1 shows that some occupations hired more women than men over time and women's wages increased more in relation men. This quadrant (lower left) is representative of the attenuation of the source of income inequality between occupations, where there is a negative relationship between the use of technological resources and wage level, but also the strengthening of the source of inequality within occupations. The concentration of occupations in the right lower quadrant means that most occupations pay better to men compared to women, although employing more women than men, from 1987 to 2011. The quadrant determines the combination of the weakening of the sources of inequality between occupations and the strengthening of inequality within occupations.

Figure 1: Sources of wage inequality at the category of high technology occupations

(Differences between 2011 and 1987 of sex ratio and gender wage gap within the occupations)


0
-1
-2
-3
-4
-5
difsexratio
-2000
-1000
0
1000
2000
difgendergap
22
87
12
44
37
10
49
17
36
83
80
13
4
47
74
21
64

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Annex:

Table A.1: Labor force distribution by wage distribution deciles, gender and race, Brazil, 1987-2011 (%)

	1987					2011				
Deciles	Non-white women	White women	Non-white men	White men	Total	Non-white women	White women	Non-white men	White men	Total
1	42.3	37.6	11.7	8.4	100.0	43.4	27.0	20.3	9.2	100.0
2	27.8	29.2	23.7	19.4	100.0	35.9	23.4	27.5	12.6	100.0
3	19.2	26.9	27.0	26.9	100.0	31.2	26.9	26.8	15.1	100.0
4	13.1	24.4	27.6	35.0	100.0	21.8	26.4	30.6	21.2	100.0
5	9.6	22.7	28.0	39.7	100.0	17.7	22.5	33.1	26.7	100.0
6	7.0	18.8	28.4	45.7	100.0	14.5	22.1	32.1	31.3	100.0
7	5.5	18.4	25.7	50.4	100.0	12.0	21.4	30.9	35.7	100.0
8	5.1	19.4	22.1	53.4	100.0	10.0	22.7	27.4	40.0	100.0
9	3.8	19.6	15.8	60.8	100.0	9.1	24.8	24.2	41.8	100.0
10	2.1	14.0	12.4	71.5	100.0	6.8	24.5	17.8	50.9	100.0
Total	14.1	23.3	22.3	40.3	100.0	20.8	24.3	27.4	27.6	100.0

Source: Brazilian Household Sample Surveys Microdata, 1987, 2011.

Table A.2: Labor force distribution by educational level, gender and race, Brazil, 1987-2011

	1987					2011				
Educational Level	Non-white women	White women	Non-white men	White men	Total	Non-white women	White women	Non-white men	White men	Total
0-3	37.5	18.8	35.9	18.7	25.1	11.7	5.9	16.3	8.2	10.6
4-7	31.3	28.8	37.8	35.0	33.6	18.4	13.0	21.8	16.5	17.5
8-10	10.9	12.2	12.1	14.2	12.8	16.2	13.1	18.9	16.0	16.1
11-14	15.9	24.3	11.5	19.2	18.3	41.2	41.4	35.8	40.3	39.5
15-+	4.4	15.8	2.8	12.9	10.2	12.4	26.5	7.2	19.0	16.3
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Source: Brazilian Household Sample Surveys Microdata, 1987, 2011.

Table A.3: Labor force distribution by nature of tasks of the occupations, gender and race, Brazil, 1987-2011

	1987					2011				
Nature of tasks	Non-white women	White women	Non-white men	White men	Total	Non-white women	White women	Non-white men	White men	Total
Routine manual	51.6	29.3	39.0	25.3	33.0	43.2	27.6	35.6	24.8	32.2
Non-routine manual	11.9	13.3	25.5	21.0	18.8	8.8	8.7	27.9	23.0	17.9
Routine non-manual	24.2	30.2	25.4	27.2	27.1	30.0	31.5	24.3	26.0	27.7
Non-routine non-manual	12.4	27.2	10.1	26.5	21.1	18.0	32.3	12.2	26.3	22.2
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Source: Brazilian Household Sample Surveys Microdata, 1987, 2011.

Table A.4: Average wages by educational level, gender and race, Brazil, 1987-2011

	1987				2011			
Educational Level	Non-white women	White women	Non-white men	White men	Non-white women	White women	Non-white men	White men
0-3	402.6	504.2	978.6	1212.4	499.1	624.1	827.0	1066.1
4-7	576.9	765.3	1308.2	1778.2	568.7	685.0	993.2	1219.8

8-10	786.3	1150.9	1724.1	2342.1	673.7	818.9	1136.8	1425.2
11-14	1318.3	1794.3	2765.6	3591.1	920.1	1202.2	1474.1	1927.2
15-+	2930.5	3251.2	5002.3	6962.3	2073.0	2869.7	3524.1	4838.3
Total	752.2	1411.5	1491.9	2751.0	906.6	1483.3	1340.1	2186.8

Source: Brazilian Household Sample Surveys Microdata, 1987, 2011.