Skill-Biased Technological Change in Brazil: Implications on Pay and Occupation Gender Gaps

Ana Hermeto
Gustavo Bressan

1. 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, increased number of women entered 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 PNAD (National Household Sample Survey) from 1983 to 2003, conducted by IBGE. This database allows a representative historical overview of changes in occupations of the Brazilian labor market.

Autor, Levy and Murnane (2003) argue that the impact of technology on the labor market can be understood as a process of replacement of human labor in routine tasks, manual or non-manual, but not in non-routine tasks (skilled an 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.

Goos and Manning (2003) support this hypothesis for median occupations, characterized by routine tasks. According to the authors, occupations are not evenly distributed along the wage distribution. Thus, routine occupations were concentrated in the middle of the distribution, non-routine occupations are concentrated in the lowest percentile, while the non-manual 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. 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 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 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 1983 to 2008 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; and (iii) to explain the potential sources of income inequality in sophisticated occupational groups by mapping occupations in terms of differential wage gap and sex ratio over time.

Literature that investigates income inequality in the labor market demonstrates the persistence of the wage gap between men and women, 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 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, i.e., if there is an interaction between occupation and gender, 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. Despite the gains by occupational segregation, women's income remains lower than the income of their male colleagues in all economic levels, in spite of reducing the difference in education levels (Black, 2000). 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 are disproportionately concentrated in low paid occupations, controlling for their individual attributes, the pay gender gap will inevitably emerge;

(ii) within occupations: men and women in the same occupation have different wage rates. Some occupations present higher wage rates than others, leading to variation in gender 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 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 according to occupational clusters. In this perspective, we attempt to demonstrate the effect of technological advancement on the pay of women.

2. Data and Methods

Microdata from the National Household Sample Survey - PNAD, of IBGE, for 1983 and 2003, were used. Labor concepts and occupational classifications have changed over the period, to adapt to the ILO standards. Moreover, during this period, there were changes in the existing range of occupations, with the appearance of new ones, weight loss of others and fusion of some previously considered distinct. This required the recoding of occupations in a new variable, taking into account such new clusters that became evident over time.

Subsequently, we assigned technological scores to the occupations[1]. The technological variables were divided into three groups: technology actions, technological labor resources and technology keywords. The scores were assigned according to Table A.1 in appendix. Using the compatible occupations, individuals were aggregated into groups of education and technology. The education groups: a low level group for individuals who have zero to eight years of study; an intermediate group, for those between nine and eleven years of schooling; and an upper level, for those with years of study greater than or equal to twelve. 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 22 scores for three strata as follows: Low, scores ranging from 0 to 4.9, Medium, 5 to 9.9 , and High. As this is a non-exact division, the High stratum was defined with a range of 12 scores. The justification is that the upper layer is less dense and could therefore have longer intervals between them. It is expected that the occupations that are associated with higher levels of education and technology are better paid.

Besides the classification of occupations according to the scores of technology, another classification was made according to the nature of their inherent tasks. This classification was based on Autor, Levy and Murnane (2003), where occupations are classified into four distinct types – manual routine, routine non-manual, routine non-manual and non-routine non-manual, as follows:

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

- Non-manual routine activities are activities that require cognitive adaptability to situations requiring completion within certain limits, standards or tolerance;

[1] This assignment followed the methodology adopted by Rodrigues (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.

- 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 non-manual activities are characterized by adaptability to accept responsibility for the management, control and planning of an activity; they may be related to education in general, development and mathematics.

Variables indicative of the requirements of an average American occupation, found in the dictionary of titles (DOT) were replicated and adapted to our occupational groups. They were used as second-level variables in our hierarchical models.

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 for the years 1983 and 2003. Throughout 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 a dummy for sex. The model is described below, where i represents the individual and j represents the period:

$$earnings_{ij} = \beta_0 + \beta_1 schooling_{ij} + \beta_2 lowtech_{ij} + \beta_3 hightech_{ij} + \beta_4 men_{ij} + e \quad (1)$$

Following the methodology of Autor, Levy and Murnane (2003) for the division of occupations according to the nature of their tasks and applying it to our compatible occupations, we reapply the econometric model (1), 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 and nature of the task (manual routine, routine non-manual, routine non-manual and non-routine non-manual). Again, the model is described below, where i represents the individual and j represents the period:

$$earnings_{ij} = \beta_0 + \beta_1 schooling_{ij} + \beta_2 manualrout_{ij} + \beta_3 routcogn_{ij} + \beta_4 nroutcogn_{ij} + \beta_5 men_{ij} + e \quad (2)$$

Quantile Regressions for Labor Force Polarization

The purpose of using a quantile regression model here is to observe how different is the impact of variables 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.

This method relaxes the assumption of normality of errors, while the regression over the median is more resistant to *outliers.* The parameters for the median are defined minimizing the sum of *absolute* errors (Least Absolute Deviations), given by:

$$\phi = \sum_{i=1}^{n} \left| y_i - x_i' \beta \right| = \sum_{i=1}^{n} \left(y_i - x_i' \beta \right) \operatorname{sgn}\left(y_i - x_i' \beta \right) \quad (3)$$

where sgn *(a)* is *the* signal of *(a):* 1 if *(a)* is positive and -1 if it is negative or zero. The condition for minimization is:

$$\sum_{i=1}^{n} x_{ij}\,\mathrm{sgn}\left(y_i - x_i^{'}\beta\right) = 0 \quad (4)$$

i.e. if there is only a constant in the regression, this equation says that this constant must be chosen such that there is an equal number of points in each of its sides (which defines the median). The quantile regression for the other percentiles is defined by minimizing

$$\phi = -(1-q)\sum_{y \le x^{'}\beta}\left(y_i - x_i^{'}\beta\right) + q\sum_{y > x^{'}\beta}\left(y_i - x_i^{'}\beta\right) = \sum_{i=1}^{n}\left[q - 1\left(y_i \le x_i^{'}\beta\right)\right]\left(y_i - x_i^{'}\beta\right) \quad (5)$$

where 0 <q <1 is the quantile of interest, and the value of the function 1*(z)* indicates the truth (1) or otherwise (0) of the proposition *(z).* The minimization condition is

$$\sum_{i=1}^{n} x_{ij}\left[q - 1\left(y_i \le x_i^{'}\beta\right)\right] = 0 \quad (6)$$

which is equal to the median when q = 0.5. If the regression only has a constant term, the constant is set such that 100.q% of the sample points are below and 100(1-q)% is above it.

Similarly to the OLS model, we estimate earnings equations by years of schooling and dummies for sex, 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 models proposed in the previous sections, where the demand for more qualified labor was exclusively determined at the individual level, our interest is to understand how the qualifications necessary for the management of technological processes and other linguistic and logical functions are remunerated differently for man to women. Our objective is to decompose the source of the wage gap under technological bias over time, i.e. how the various required skills are paid by gender, 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 (Hox, 1995). 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 the compatibilized occupations (*compocc*) as the second level and earnings as the dependent variable, in specific estimates by gender and period.

The estimation method is the restricted likelihood. The method allows that second level observations have different random intercept and elasticity coefficients. Besides, the error terms depend on both the individual level, as the occupational, creating a problem of heteroscedasticity. The difficulty is overcome by MV estimators, which are consistent and asymptotically efficient. The first model is the ANOVA, with random effects. The model is represented as follows:

$$Y_{ij} = \beta_{0j} + r_{ij} \quad (8)$$

$$\beta_{0j} = \alpha_{00} + u_{0j} \quad (9)$$

where i denotes individuals, j denotes occupations, and β_{0j} the mean of the dependent variable (earnings) across the groups. Beyond the estimation of the coefficient α_{00}, the estimation of this simple model 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. The coefficient is expressed by:

$$\rho = \tau_{00}/(\tau_{00}+\sigma^2) \quad (10)$$

The main model can be understood as a system of linear regressions. Given the regression expressing the causality between X and Y on the lower level, it is allowed that β_0 to vary in accordance with a new set of variables Z, at the upper level. The system of equations is now:

$$Y_{ij} = \beta_{0j} + \beta_1 X_{ij} + r_{ij} \quad (11)$$

$$\beta_{0j} = \alpha_{00} + \alpha_{10} Z_j + u_{0j} \quad (12)$$

The assumptions of errors with zero mean and constant variance are valid for all three equations; errors in (12) are independent of those in (11), the covariance between u_{0j} and u_{1j} however, is different from zero. The indices i and j denote the model hierarchy. At the lowest level, represented by equation (11), the beta coefficients depend on the observations j, which gives them the description of random coefficients; and Y depends on i and j. At the upper level, the coefficients do not depend on the observations, i.e. the same coefficient is valid for the entire sample. Writing (11) according to (12) yields:

$$Y_{ij} = [\alpha_{00} + \alpha_{10} Z_j + u_{0j}] + \beta_1 X_{ij} + e_{ij} \quad (13)$$

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 of individuals. At the individual level (equation 9) it is estimated the logarithm of deflated earnings as a function of individual human capital, age and an error with random distribution:

$$Y_{ij} = \beta_{oj} + \beta_{1j}(schooling) + \beta_{2j}(age) + \beta_{3j}(age^2) + r_{ij} \quad (14)$$

where i indexes individuals and j indexes occupations in technology groups, the error r_{ij} is assumed to be random normal with zero mean and constant variance.

The second level reflects the sensitivity of the parameters that characterize a group of occupation to remunerate men and women differently, in order to investigate the increase in the remuneration of women in occupations more sophisticated. The technological and educational requirements necessary for the performance of the work required in these occupations specifies the second level:

$$\beta_{0j} = \alpha_{00} + \alpha_{01}(medtech) + \alpha_{02}(hightech) + \alpha_{03}(FF) + \alpha_{04}(REGR) + \alpha_{05}(REGM) + \alpha_{06}(REGL) + \alpha_{07}(AES) + \alpha_{08}(AEX) + u_{0j} \quad (15)$$

$$\beta_{0j} = \alpha_{00} + \alpha_{01}(mannrout) + \alpha_{02}(routcogn) + \alpha_{02}(nroutcogn) + \alpha_{03}(FF) + \alpha_{04}(REGR) + \alpha_{05}(REGM) + \alpha_{06}(REGL) + \alpha_{07}(AES) + \alpha_{08}(AEX) + u_{0j}$$

where j indexes occupations grouped into occupational categories. The first 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. β_{0j} is the intercept term of the equation at the individual level (representing average occupational income adjusted for individual attributes), and u_{0j} is a specific error by occupation, with normal distribution, mean 0 and constant variance.

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, 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. 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 ratio or to different wages within the occupation.

We compute the differential of the wage gap between men and women in the occupations of the groups in analysis and the differential of the sex 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. The quadrants formed state:

• Negative differential wage gap and positive sex ratio (upper left): women in 2003 earn more relative to men than in 1983, 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 2003 earn more relative to men than in 1983, 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 2003 earn less relative to men than in 1983, 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 2003 earn less relative to men than in 1983, 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.

3. 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 1983 and 2003. 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). Table 1 depicts the increase in intensity of the correlation between wages and technological tools and processes. Moreover, the increase in 2003 of the mean scores of technology signals an increased use of technology resources throughout the wage distribution. The result therefore provides a strong indication of the technological bias, the basic assumption of this study and also suggests the displacement of the labor force in favor of technological occupations.

Table 1: Average scores by wages deciles, Brazil, 1983-2003

Deciles	1983	2003
1	1,41	0,96
2	1,14	1,15
3	1,21	1,35
4	1,54	1,63
5	1,58	1,94
6	1,99	2,25
7	2,40	2,67
8	2,86	3,30
9	3,61	4,33
10	5,29	6,14

Source: PNADs. IBGE, 1983, 2003.

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. Table 2 lists technology groups and average wages by year. We assume they are historical reasons for the incompatibility of the results with actual increases expected for the more sophisticated occupations at the expense of low and medium, given the flatting wages prior to 2003 due to inflationary shocks and the swelling of the labor force caused by entry of young people in the labor market more than proportional to retirement during the twenty years included in this panel. For all categories and years, male wages are higher than the female 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. 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 technology groups and sex, Brazil, 1983-2003

	1983			2003		
	Total	Men	Women	Total	Men	Women
Low	537,62	636,79	343,22	465,15	532,36	366,73
Medium	1574,06	1755,99	998,82	1293,28	1474,30	979,51
High	2093,41	2339,18	1413,90	2027,96	2205,23	1747,14

Source: PNADs. IBGE, 1983, 2003.

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 groups and dummy for sex via OLS. The dummy for sex is to demonstrate the difference in level in favor of males. Based on (1), the regressions separately for the years shown in Table 3, yielded coefficients lower than the average group (control group) for individuals classified in the lower strata. Over time the relative coefficient does not present a variation pattern. 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. The results show a higher propensity of individuals in the most technologically advanced occupations to hold higher wages, with positive bias over time.

Table 3: Results of Wages Regressions, Brazil, 1983-2003

	1983	2003
Years of schooling	82,859***	62,118***
	(0,748)	(0,578)
Technology level: low	646,274***	-634,212***
	(0,09)	(0,07)
Technology level: high	255,341***	637,586***
	(0,30)	(0,19)
Men	446,031***	333,395***
	(0,06)	(0,05)
Constant	511,718***	495,412***
	(0,12)	(0,10)

Source: PNADs. IBGE, 1983, 2003.

Note: Standard erros in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

In both econometric models all dummies for gender indicated higher male to female earnings. However, there is a downward trend in the gender gap, as confirmed by the analysis of the dummies in temporal perspective. 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. Results are shown in table 4:

Table 4: Distribution of labor force by technology group, Brazil, 1983-2003

Strata	1983	2003	Δ over time
Low	86,23	82,08	-4,15
Medium	12,41	15,96	3,55
High	1,36	1,96	0,60

Source: PNADs. IBGE, 1983, 2003.

Interestingly, the flow of women into more sophisticated occupations over time, almost reaching men for the analysis of the technology groups, as shown in Table 5. Based on this fact, we will test whether the increase in demand for more qualified for the duties of 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 to the decrease of the average gap between men and women over time.

Table 5: Sex ratio by group of technology and education, Brazil, 1983-2003

Strata	1983	2003
Low	0,94	0,97
Medium	1,60	1,15
High	1,40	1,05

Source: PNADs. IBGE, 1983, 2003.

Following the methodology of Autor, Levy and Murnane (2003) for the division of occupations according to the nature of the task and applying it to the Brazilian occupations, it is estimated the equation (2), in order to prove once more 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 presented in Table 6, in this sense, confirms the trend. The coefficient on the dummy for routine non-manual occupations falls significantly, the coefficient of the dummy for routine manual occupations decreases only marginally and is, however, since 1983, negative controlled relative to the non-routine manual stratum. Still, according to the model the non-routine non-manual occupations are better paid recently.

Table 6: Results of Wages Regressions by Nature of Tasks, Brazil, 1983-2003

	1983	2003
Years of schooling	74,332***	61,903***
	(0,698)	(0,633)
Routine Manual	-11,450	-10,366
	(7,564)	(7,789)
Routine Non-manual	7,363	-22,716***
	(6,974)	(7,254)
Non-Routine Non-manual	751,918***	795,682***
	(9,922)	(9,206)
Men	482,883***	373,854***
	(5,415)	(5,104)
Constant	-124,516***	-172,365***
	(8,022)	(8,668)

Source: PNADs. IBGE, 1983, 2003.

Note: Standard erros in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

The analysis of distribution of the labor force in the four strata, seen in Table 7, confirms the hypothesis of polarization in the way proposed by Autor, Levy and Murnane (2003) for Brazil. The table below shows the increase in demand for "non-routine non-manual" occupations and a slight drop in "non-routine manual" (so-called extreme occupations). The occupations said to be medians – "routine manual" – showed a slight increase and those which are “non-manual routine" showed a marked thinning.

Table 7: Distribution of the labor force by nature of the tasks, Brazil, 1983-2003

Strata	1983	2003	Δ over time
Manual routine	26.18	27.66	1.48
Manual non-routine	16.12	15.91	-0.21
Non-manual routine	45.83	39.78	-6.05
Non-manual non-routine	11.88	16.65	4.77

Source: PNADs. IBGE, 1983, 2003.

Quantile Regressions

As noted in Table 1, 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, poorest 50% or 50% richest 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 and dummies for sex and nature of the task. The quantiles of interest were the first (0.1), referring to the poorest 10% of the population, the fifth (0.5), for which it assigns equal weight to the lower and upper 50% of wage income, and the tenth (0.9), referring to the richest 10%.

What can be seen in Table 8 is the increasing polarization of income for the top decile of the wage distribution in Brazil. 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, as expected, and in all examined quantiles, the downward trend of the gender gap is sustained.

Table 8: Results of quantile wage regressions by nature of tasks, Brazil, 1983-2003

	0.1		0.5		0.9	
	1983	2003	1983	2003	1983	2003
Years of schooling	17,703***	12,467***	40,787***	30,000***	112,561***	77,364***
	(0,038)	(0,101)	(0,000)	(0,000)	(0,249)	-1,001
Manual Routine	-0,000	20,400***	-9,104***	0,000	-37,741***	-61,091***
	(0,431)	-1,480	(0,000)	(0,000)	-2,412	-10,114
Non-manual routine	-17,703***	-70,000***	-32,411***	-70,000***	35,093***	-79,545***
	(0,404)	-1,395	(0,000)	(0,000)	-2,274	-9,631
Non-manual non-routine	74,232***	121,733***	484,707***	430,000***	1669,710***	1990,545***
	(0,582)	-1,773	(0,000)	(0,000)	-3,193	-12,193
Men	109,639***	78,867***	214,130***	170,000***	550,387***	381,545***
	(0,292)	(0,951)	(0,000)	(0,000)	-1,787	-7,098
Constant	2,020***	-8,867***	68,828***	70,000***	183,408***	199,545***
	(0,447)	-1,564	(0,000)	(0,000)	-2,750	-12,756

Source: PNADs. IBGE, 1983, 2003.

Note: Standard erros in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Hierarchical Models

To test the impact of technological advances on the allocation and remuneration of women, we used hierarchical models. Since it was captured 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.

The ANOVA model with random effects reported in Table 9 attests the reduction of the wage gap between men and women between 1983 and 2003. The intra-class correlation coefficient, however, provides 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 1983 to 2003 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: Results of the ANOVA model with random effects, Brazil, 1983-2003

	1983	2003

	Men	Women	Men	Women
Constant	1048.359***	529.7835***	886.689***	805.654***
	(10.97)	(5.33)	(9.36)	(7.18)
Variance components				
Individual level	1631295.7***	281577.94***	1137520.9***	404000.1***
	(15770.27)	(3782.21)	(11919.29)	(5058.66)
Occupational level	311852.92***	228580.15***	606513.11***	806566.19***
	(9086.70)	(6192.96)	(19893.06)	(21217.46)
Intra-class coefficient	0.160	0.448	0.348	0.666

Source: PNADs. IBGE, 1983, 2003.

Note: Standard erros in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

The main model 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 of Equation 15, shown in Table 10, reveals the opposite of 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 null on the remuneration of the use of advanced technological resources for women, and the gender difference grows. It is worth noting that the awards on the grammatical and logical requirements become significant for women from 2003 to 1983, being larger than the male, an indication that women have become more well-paid in more complex occupations, but which, however, does not require administration of a wide range of technologies for its performance. This hypothesis can only be proven with the estimation of the equation, which, instead of using technology groups, makes use of the groups according to the nature of the tasks in the occupation.

Table 10: Results of Hierarchical Wage Regressions by Groups of Technology, Brazil, 1983-2003

	1983		2003	
	Men	Women	Men	Women
	1st Level			
Years of schooling	113.043***	57.816***	67.261***	51.398***
	(3.51)	(2.68)	(4.31)	(3.58)
Age	85.425***	44.208***	79.994***	40.023***
	(9.04)	(6.79)	(13.37)	(11.53)
Age2	-0.873***	-0.472***	-0.809***	-0.362**
	(0.11)	(0.09)	(0.16)	(0.14)
	2nd Level			
Constant	-1737.161***	-879.476***	-1023.923***	-1523.441***
	(188.04)	(140.75)	(289.63)	(248.56)
	46.219	-71.747	-215.674***	71.824
Technology level: medium	(50.04)	(38.46)	(72.58)	(52.71)
	581.186***	364.632***	752.959***	209.305*
Technology level: high	(127.15)	(99.38)	(148.70)	(126.83)
FF	-35.336	69.821***	-219.459***	237.708***

	(29.42)	(23.42)	(45.60)	(39.56)
REGR	199.007***	8.965	-140.274**	277.675***
	(46.10)	(23.97)	(65.07)	(42.93)
REGM	-0.382	455.328***	124.880***	101.904**
	(31.72)	(35.31)	(45.44)	(43.47)
REGL	281.497***	25.633	293.651***	367.843***
	(50.98)	(35.41)	(70.80)	(58.65)
AES	-28.087***	-5.708	-11.983	-25.624***
	(5.62)	(4.80)	(7.97)	(9.51)
AEX	42.896***	-5.003	16.085	23.842
	(12.88)	(15.24)	(19.54)	(18.61)
Variance components				
Individual level	1070065.4***	272887.19***	756704.2***	325527.56***
	(14061.11)	(5483.34)	(17494.68)	(9397.84)
Occupational level	72852.151***	44964.764***	89415.122***	168242.44***
	(7939.63)	(5203.50)	(15767.07)	(21649.66)
Intra-class coefficient	0.064	0.141	0.106	0.341

Source: PNADs. IBGE, 1983, 2003.

Note: Standard erros in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

The variance that was not previously captured by the variables of technological groups, which suggested rising premiums to the requirements of grammar and logic, is now captured by the nature of tasks variables. As can be seen in Table 11, the returns associated with non-manual non-routine activities converge for men and women over time. 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.

Table 11: Results of Hierarchical Wage Regressions by Nature of Tasks, Brazil, 1983-2003

	1983		2003	
	Men	Women	Men	Women
	1st Level			
Years of schooling	113.115***	58.684***	68.845***	51.112***
	(3.52)	(2.79)	-(4.28)	-(3.65)
Age	85.927***	45.649***	77.519***	43.135***
	(8.93)	(7.24)	-(13.37)	-(11.61)
Age2	-0.881***	-0.492***	-0.782***	-0.397***
	(0.11)	(0.09)	-(0.16)	-(0.14)
	2nd Level			
Constant	-1557.735***	-261.578*	-1573.730***	-1077.736***
	(207.79)	(152.98)	(284.70)	(282.57)
	142.940**	-406.096***	181.273***	-442.361***
Manual non-routine	(56.45)	(36.20)	(67.20)	(66.47)
	2.183	-529.765***	-281.175***	68.101
Non-manual routine	(39.79)	(39.53)	(69.58)	(51.13)
Non-manual non-	562.739***	-282.461***	236.442*	228.008**

routine	(72.46)	(43.07)	(136.26)	(95.43)
FF	5.103	-268.112***	-6.734	32.413
	(32.89)	(20.65)	(41.77)	(38.65)
REGR	-235.930***	68.131**	-126.41783	51.985
	(64.21)	(26.56)	(79.46)	(43.05)
REGM	150.656***	374.202***	291.881***	466.268***
	(56.89)	(36.36)	(59.50)	(65.69)
REGL	331.918***	305.224***	601.341***	120.416*
	(68.32)	(39.93)	(110.70)	(65.24)
AES	-26.891***	-37.929***	-38.593***	-37.383**
	(9.33)	(5.26)	(11.03)	(17.99)
AEX	49.483***	9.583	27.294	45.514
	(14.62)	(13.73)	(18.56)	(31.95)
Partição da variância				
Nível individual	1071673.4***	272051.58***	763254.15***	327528.13***
	(14116.67)	(5453.86)	(17741.28)	(9488.02)
Nível ocupacional	68332.989***	92520.03***	77320.064***	114016.4***
	(13646.11)	(12267.59)	(20094.27)	(17226.20)
Coeficiente intraclasse	0.060	0.254	0.092	0.258

Source: PNADs. IBGE, 1983, 2003.

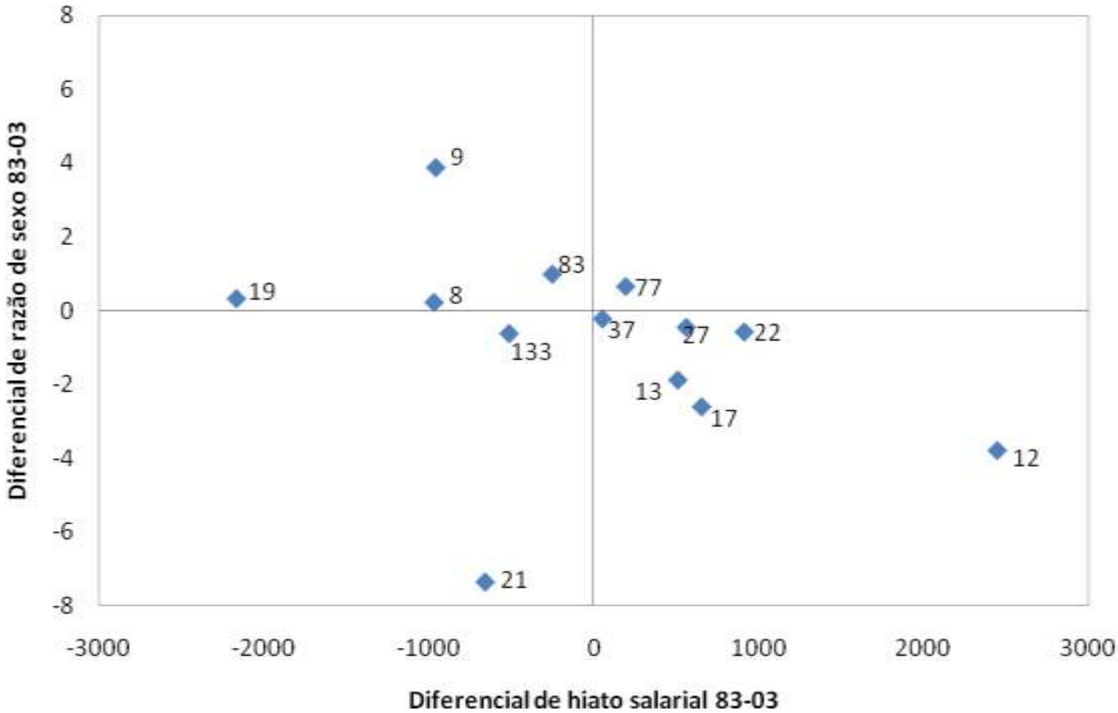
Note: Standard erros in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

We can conclude that the impact of polarization with technological bias in the fall of the gender gap over time is due more to the requirements of complex occupations than to the use of technological resources. In this perspective, despite the higher allocation of women in high technology stratum in 2003 (Table 5), these occupations are culturally associated with men, and the prejudice within the occupations that employ more technological resources becomes prominent.

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, both proven in previous sections, we will map occupations primarily in the stratum technological and later in occupations non-manual non-routine, 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 stratum technological rewarded fewer women from 1983 to 2003 regarding the use of technology. The graphical analysis deepens the analysis of the sources of wage inequality and occupations in which they influence (Figure 1):

Figure 1 - Sources of income inequality – high technological stratum

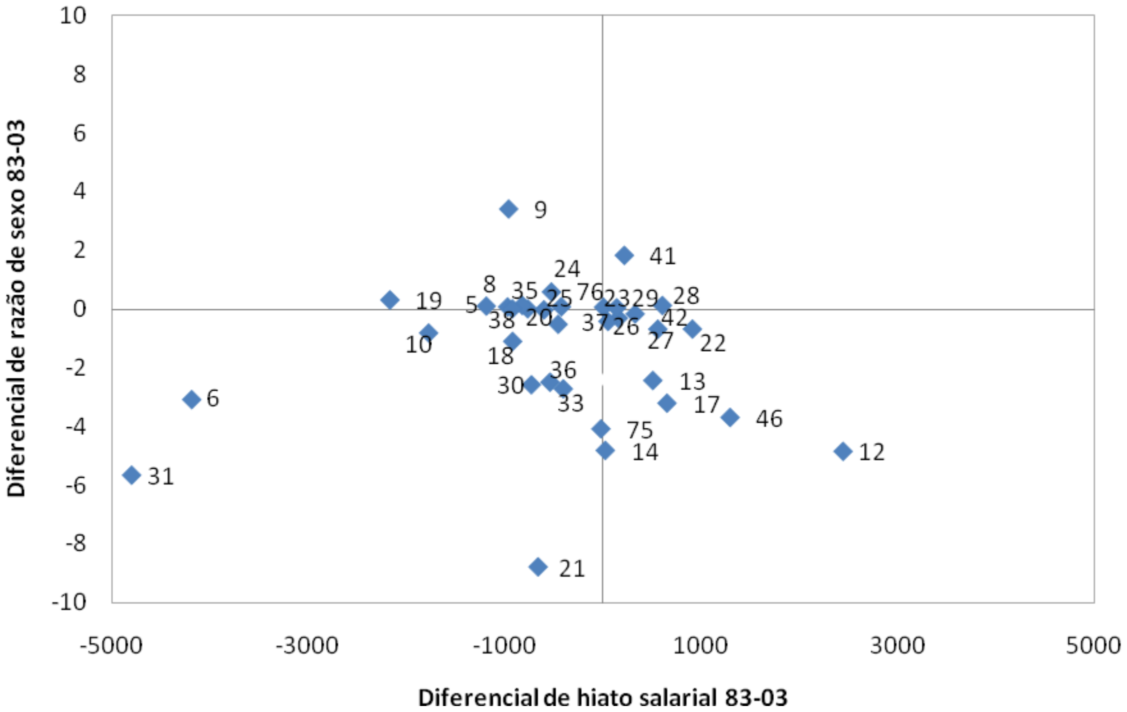


For instance, the occupations 8 (biologists), 9 (computer programmers), 19 (pharmacists and pharmacologists) and 83 (quality inspectors) hired more men than women in the twenty years between the points of analysis, while women's wages increased more in relation men. This quadrant (upper left) is representative of the intensification of the source of income inequality between occupations, where there is a positive relationship between the use of technological resources and wage level, but also the weakening of the source of inequality within occupations .

The highest concentration of occupations occurs, however, in the right lower quadrant. The occupations 12 (Systems Analyst), 13 (chemical, physical, other experts in chemistry and physics, meteorology technicians, geographers and demographers), 17 (physicians), 22 (other medical specialists) and 27 (teacher researchers) pay better to men compared to women, although employing more women than men, from 1983 to 2003. The quadrant determines the combination of the weakening of the sources of inequality between occupations and the strengthening of inequality within occupations.

In more complex occupations, in which there is not necessarily the use of many technological resources, it was pointed an increasing bonus pay for women relative to men. The mapping of these occupations and the sources for wage inequality that affect them are shown below.

Figure 2 - Sources of income inequality – non-manual non-routine stratum



Compared to the previous figure, what stands out is the high concentration of occupations in the lower left quadrant, representing the weakness of the sources of wage inequality between and within occupations. The occupations 10 (architects), 18 (dentists), 20 (qualified nurses), 21 (veterinary), 30 (lawyers and public defenders), 31 (delegates and police commissioners) and 33 (heads and directors of administrative services section of companies) fall into this reality of gender wage approach.

Closer to the horizontal axis, the occupations of the upper left quadrant is representative, like its predecessors, of the weakening of the source of inequality within occupations, with a slight intensification of the source of income inequality between occupations, since, as noted before, non-routine non-manual occupations are at the top of the income distribution. It stands out in this situation occupations 5 (directors, advisors and leaders in public service), 25 (teachers in the first degree), 34 (psychologists) and 35 (social workers).

It is also important that the right lower quadrant, which, although attests to the positive change of the wage gap between 1983 and 2003, shows the highest allocation of women in sophisticated occupations that pay better. They are in this quadrant, especially, the occupations of the stratum previously identified as high technology, and also classified as non-routine non-manual.

4. Final Remarks

The central objective to evidence the polarization in the Brazilian labor market in favor of more sophisticated occupations was accomplished by first estimating OLS regressions, which showed the increase in demand in occupations that require more technological tools and processes. Results were revealed mainly by the increase in premium given to professionals engaged in high technology occupations, in comparison, from 1983 to 2003.

A check of the polarization hypothesis was further enhanced with the use of a technological categorization of occupations according to the American dictionary of occupational titles (DOT), in order to replicate the findings from the literature of that country for consolidated polarization of the labor market under technological bias. In line with the results of the Autor, Levy and Murnane Levi (2003) and Goos and Manning (2003), there can be seen an increase in demand for non-routine occupations, i.e. those for which the performance of their duties is not perfectly interchangeable with the existing technology.

The strong relationship between the use of technological resources in an occupation and wages, that is assumed by the polarization hypothesis, was confirmed with the estimation of the average sum of the technological elements necessary for the performance of an occupation, according to the Brazilian classification of occupations (CBO), by deciles of the wage distribution. The result towards the consolidation of this hypothesis was highlighted by the estimation of quantile regressions for wages and dummies for groups of occupations, which strengthened the premium associated with non-routine non-manual occupations up in the percentiles of the wage distribution.

Regarding the analysis of the impact of increased polarization of the labor market on the remuneration of men and women, the ANOVA model with random effects yielded intra-class correlation coefficients that suggested that the remuneration of women vs. men is more susceptible to occupational characteristics. Therefore, it is possible to assume that the bonus in pay traditionally assigned to men allows a greater wage variation regardless of occupational characteristics. The strength of this bonus, however, declined from 1983 to 2003.

The hierarchical models showed that the impact of polarization with technological bias in the fall of the gender gap over time is due more to the requirements of complex occupations, than to the use of technological resources. The key results that strengthen this conclusion are: (i) the increase in the gender pay gap to the use of technological resources, captured by the dummy on the top technology group, coupled with the significant gain of specific skills, such as requirements of logical and grammatical for women over time, and (ii) a decrease in the gender pay gap in terms of the bonus associated with non-manual non-routine complex occupations.

To the analysis of the variation in pay for men and women, it was added the check of the allocation of women in the group of sophisticated occupations. In a 2x2 matrix they were plotted occupations in order to explain dichotomously sources of wage inequality: between occupations, due to the reduced presence of women in these sophisticated or technological occupations, which pay better, or within occupations, where men earn more than women performing the same function.

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APPENDIX:

Table A.1: Scores of technological variables

Technology stocks	***Scores***
Following technological trends	4
Construction equipment	3
Control (control) quality	2
Control parameters	3
Develop research activities	5
Develop improvements in the productive process	4
Develop processes	4
Develop products and systems	4
Perform maintenance	A
Draw / draw up technical documents	2
Fabrication and assembly	A
Manufacture of machinery and equipment	2
Manufacture of	A
Identify opportunities to apply (this) technology	5
Operate equipment	A
Researching new technologies	3
Programming (production, machinery, system, computer, visual graphics)	3
Production schedule	3
Promote technological changes	5
Providing technology solutions	5
Test (systems, engines, performance, operation of machines)	3
Guidelines outline the scientific and technological	4

Technological resources work	***Scores***
Beep	0.5
Computer	A
Datashow	2
Fax	0.5
GPS	2
Optical precision instruments	3
Internet	A
Laptop / Notebook	2
Laser	2
Technical literature	A
Machine	0.5
Technical Manuals	A
Publications (scientific and other)	3
Robot / Robotic	3
Software	2

Keywords technological	***Scores***
Aeronautics	2
Extension Activities	3
Research activities	4
Technology activities	5
Technical activities	2
Industrial automation	A
Automatic	A
Biotechnology	4
Science and Technology	5
Scientific (a) (s)	2
Nuclear fuel	3
Expertise	2
Digital / Digital	A
Special effects	3
E (a)	0.5
Manufacturing industry	2
Computers	A
Technological Innovation	5
Medical, hospital	3
Laboratory	3
Production line	3
Mechanization	A
Modelista product	A
Modernization	3
Multidisciplinary	2
Scientific research	5
Research and development	5
Technical procedures	2
Production Process	2
Semi Automatic	0.5
System (s) to	4
System (s) of quality	A
Operating Systems	3
Technique (s)	A
Production engineers	4
Technology / Technological (s) / Programme (s)	3
Telecommunications	A

Source: Rodrigues (2006).