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Gender and Racial Wage Gaps in Brazil 1996-2006: Evidence Using a Matching Comparisons Approach

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Abstract[1]

This paper explores the evolution of Brazilian wage gaps by gender and skin color over a decade (1996-2006), using the matching comparison methodology developed by Ñopo (2008). In Brazil, racial wage gaps are more pronounced than those found along the gender divide, although both noticeably decreased over the course of the last decade. The decomposition results show that differences in observable characteristics play a crucial role in explaining wage gaps. While in the case of racial wage gaps, observable human capital characteristics account for most of the observed wage gaps, the observed gender wage gaps have the opposite sign than what the differences in human capital characteristics would predict. In both cases the role of education is prominent.

Keywords: Gender, race, wage gaps, Brazil, matching
JEL codes: C14, D31, J16, O54

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1. Introduction

Promoting gender and racial equality has been one of Brazil's major challenges. While some believe that this challenge is starting to be met, others believe that the work of implementing effective policies has just begun. At the same time, a substantial portion of the population does not even believe that inequality is a serious problem (Márquez et al., 2007). Like other countries in the region, Brazil's history has included several centuries of slavery involving both indigenous peoples and Afro-descendants, and the legacy of slavery persists in more and less subtle forms of discrimination. Although grassroots movements have denounced these problems for decades, only recently has the Federal Government launched an innovative and coordinated National Policy for the Promotion of Gender and Race Equality. For the first time, the Multiyear Plan (PPA) for 2004-2007 included in its goals "Social Inclusion and Reduction of Social Inequalities." The central objective of the National Policy for Promotion of Gender and Race Equality is to reduce gender and racial inequalities in Brazil, with emphasis on the Black population, and the policy's success will depend on coordinated action and commitment by all spheres of government and society.

A popular perception in Brazil is that racism does not affect a person's life and that study, hard work and initiative are the main factors leading a person to success.[2] Nonetheless, the research conducted so far suggests wage gaps that, depending on the source, are around 50 percent between white and Black males and 45 percent between white and Black females in the mid-2000s. It is also found that race and gender significantly affect income, even when education, experience and labor market characteristics are taken into account. In Brazil, understanding the reasons why Blacks and women are paid less than whites and men in similar conditions is extremely important. Contrary to popular belief, discrimination may exist not only because of the legacy of slavery, but also because of contemporary forms of discrimination. Thus, women and Blacks are limited in their access to "elite" universities and executive jobs. Consequently, any attempt to disentangle wage differentials and shed light on these questions will help researchers to inform public policies.

We analyze the wage differential evolution by gender and skin of color over a decade (1996-2006) using the National Household Sample Survey (PNAD) conducted by the Brazilian

[2] There is an emerging popular belief, however, that although racial differences are unimportant for people's opportunities for success and wellbeing, there are class differences that prevent people from progressing.

Institute of Geography and Statistics (IBGE). We use the matching comparison methodology developed by Ñopo (2008), a non-parametric alternative to the Blinder-Oaxaca decomposition that emphasizes the role of the differences in the supports of the distribution of observable human capital characteristics. The method chosen will not only decompose the wage gap into endowments and an unexplained block but will also allow us to explore the distribution of the unexplained differences in wages. Additionally, our approach accounts for the outcomes of Blacks and women for whom no whites or males with comparable human capital characteristics can be found, an issue often neglected in the wage gaps literature.

This paper is organized as follows. The second section reviews the literature on racial and gender gap in pay in Brazil is reviewed, while the third section summarizes the methodology and empirical models. The fourth section presents the data and empirical findings, and the fifth section concludes.

2. Gender and Racial Differences in Pay in the Brazilian Labor Market: A Review of the Literature

The most prominent tool for the analysis of wage gaps has been the decomposition introduced by Blinder (1973) and Oaxaca (1973). This technique breaks wage differentials into two components: one that can be explained as the result of differences in average observable human capital characteristics between the comparing groups and another that cannot be explained in light of observable characteristics and hence could be attributed to the existence of unobservable elements in the labor market, discrimination being one of them.

Following the Oaxaca-Blinder decomposition approach (hereafter OB decomposition), one of the most comprehensive analysis on gender and racial wage differentials in Brazil is Soares (2000). He documents that, beginning in the 1980s, racial wage gaps have been on average higher than gender wage gaps. White women earn 79 percent and Black men only 46 percent of white men's earnings. While gender wage gaps tend to decrease over time, racial differentials seem to remain constant. The OB decomposition shows very different patterns for gender and racial differentials in wages. The explained component of the gap dominates for racial differentials, whereas by gender the unexplained component is constantly greater than the explained one.

Similarly, in a more recent study, Carvalho et al. (2006) analyze gender and racial wage gaps by applying the OB decomposition correcting for the selection bias as proposed by Heckman (1979).[3] The correction for labor market participation reveals that the unexplained component reduces the gender gap of whites from 37 percent to 30 percent and the racial gap of males from 33 percent to 18 percent but increases the wage gap of white men to Black women from 78 percent to 95 percent.

Several studies by Lovell (1994, 2000 and 2006) analyze gender and racial differences in wages by using census data instead of national household surveys. In her empirical applications, she adopts a modified version of the standard OB decomposition as proposed by Jones and Kelly (1984, quoted in Lovell, 1994). Lovell (1994) claims that gender wage gaps are greater than racial wage gaps by employing sample data from the 1960 and 1980 censuses. This finding suggests that before 1980 wage differences by gender were predominant. Another study with Wood (Lovell and Wood, 1998) highlights how the unexplained component of both gender and racial wage gaps is increasing over time. Lovell (2000) focuses more on regional differences of wage gaps, considering only the states of São Paulo and Bahia. The richer state, São Paulo, shows greater wage differentials and a larger unexplained component. In her most recent study, Lovell (2006) focuses on wage gaps only in the labor market of São Paulo, but covering a larger time period. Her findings are in line with previous studies: over time racial differentials are stable while gender differentials seem to decrease. In particular, the unexplained component is increasing over time. Along similar lines, Calvalieri and Fernandes (1998) also report wage gaps that are higher along gender than racial lines. By employing the PNAD for 1989, they estimate earning equations and find that, after controlling for a large set of characteristics, the gender wage gap becomes larger than the racial wage gap. This is probably due to the greater variation of the racial wage gap in comparison to the gender wage gap, which is captured by regional dummies included in the regression equations.

Looking at studies that only focus on gender differentials, Camargo and Serrano (1983) first investigate gender pay differentials without applying the OB decomposition. They specify wage equations using not only personal characteristics, such as level of education, but also aspects of firms' sectoral structure such as concentration, capital intensity and sector size. Their

[3] This study also controls for the usage of complex sample surveys without finding any significant alterations in the estimated coefficients.

findings suggest that the structure of economic sectors plays a negligible role in the determination of female wages. One of the first studies exploring gender pay gaps by using the OB decomposition is Birdsall and Fox (1985). Extracting a 1 percent sample from the 1970 Brazilian census, focused on a specific occupational category (in this instance schoolteachers), the authors found an explained component greater than the unexplained one. As 74 percent of the wage gap can be explained, the authors claim that job discrimination (proxy measured by the unexplained component) does not represent the main source of gender earnings differentials for school teachers.

Stelcner et al. (1992) examine gender differentials in wages using the 1980 Census by correcting the earning equation estimations for the selection bias. Unexplained components are greater than the total wage differentials, and a negative explained component highlights the better position of women in terms of endowments. These findings are supported by evidence that women have become more educated than men since the 1980s.[4] Birdsall and Behrman (1991) also pay special attention to correction for non-random selection. They first correct the estimation of wage equation for labor market participation, in the case of men considering participation in the formal or informal market, and in the case of women considering formal, informal or domestic work.

By exploring differences across the formal and the informal labor market, Tiefenthaler (1992) finds that gender earnings differentials tend to be greater in the formal sector. Interestingly, the unexplained component dominates in the formal sector, while the explained component dominates in the informal sector, a finding supported by evidence that better-educated women tend to work in formal occupations.[5] Barros, Ramos and Santos (1995) investigate the role played by education and occupational structure in the evolution of gender differentials. Apart from confirming previous results on the effect of education on gender pay

[4] Several empirical studies report women's educational attainment higher than those of men for Brazil. Beginning in the 1980s, women's educational achievement consistently exceeds that of comparable men (Beltrão and Teixeira, 2004; Henriques, Paes de Barros and Azevedo, 2006). Beltrão (2003), analyzing the spread of education and literacy in Brazil from 1940 to 2000 using Census data, finds that women overtake men around 1991 and whites still have more years of education than non-whites. Beltrão and Teixeira (2004) use 1960-2000 Census data to analyze the evolution of education by cohort and find that women, having reversed previous trends, are now more educated than men, while non-whites continue to have fewer years of education than whites.

[5] Further studies by Kassouf (1997; 1998) and Silva and Kassouf (2000) have corrected the wage equation estimation for participation in the formal and informal labor market sectors.

gaps, they provide evidence for the "glass ceiling" phenomenon that prevents women from reaching managerial positions.

Another study on the effects of occupational structure on gender wage gaps was undertaken by Ometto, Hoffmann and Alves (1999), adopting the OB decomposition technique as revised by Brown et al. (1980). This reformulation isolates the extent of pay gaps by gender due to inter-occupation and intra-occupation discrimination. The empirical exercise is made by comparing the São Paulo area with Pernambuco. In the less wealthy area of Pernambuco, gender wage gaps are mainly the results of intra-occupational discrimination, while in São Paulo both kinds of discrimination play a crucial role. Leme and Wajnman (2000) also stress the role of education endowment in determining pay gaps by cohort. They confirmed findings of previous studies claiming how education is not able to explain gender pay gaps for Brazil. Returns to education are favorable for women, and gender pay gaps are due to the unexplained component and not to endowment differences. They analyze differentials by different cohort and find that returns to education are more favorable to women in cohorts born after the 1950s, a finding compatible with improvements in women's educational attainment over time.

The most recent and comprehensive study investigating gender wage gaps over a decade is provided by Arabsheibani, Carneiro and Henley (2003). Over time gender differentials in wages noticeably decrease, mainly due to the decrease of the explained component. Women's endowments, particularly educational achievement, have had an important effect. Finally, Loureiro, Carneiro and Sachshida (2004) compare gender gaps in urban and rural areas, finding larger wage gaps in the former.

Looking at empirical studies focusing only on racial differentials, Silva (1980) represents the pioneering study on racial wage gaps that applies the Blinder-Oaxaca decomposition technique. He employs a 1.27 percent sub-sample of the 1960 Census and restricts his analysis to male workers living in the Rio de Janeiro metropolitan area. The racial groups considered are three: whites, *mulatos* (persons of "brown" complexion and presumptively of mixed European and African ancestry) and *negros* (darker-skinned individuals appearing to be primarily or exclusively of African ancestry). Silva finds a greater wage gap for *negros* than for *mulatos* with respect to white male workers. At the same time, the explained component is larger than the unexplained component, especially for *negros*.[6]

Silva's seminal work was not updated until Arias, Yamada and Tejerina (2004), who take into account for the entire wage distribution by exploiting the quantile regression methodology developed by Koenker and Bassett (1978). Their findings support the importance of examining different points of the earnings distribution and not simply average values, as in the OB decomposition technique. The bottom decile of Blacks earn 24 percent less than comparable whites, while the top decile of Blacks earn 56 percent less. Furthermore, Blacks earn 46 percent less than whites, while persons of mixed race earn 42 percent less. Persons of mixed race at the bottom of the earnings distribution have similar earnings to those of Blacks, but persons of mixed race at the upper end of the income distribution have earnings similar to those of whites. Arcand and D'Hombres (2004) enrich the study of racial earning differentials made with OB decomposition and quantile regression by considering the selection bias correction for occupational attachment. While explained components account for the greater part of the gaps among both Blacks and those of mixed race, the unexplained component is greater for Blacks.

Expanding on Soares (2000), Campante, Crespo and Leite et al. (2004) focus on differences between the North-East and the South-East regions. In the South-East region the racial gap is greater than the national average, and the unexplained component tends to be greater. In addition, Leite (2005) proves that the unexplained component is higher for the South-East than for the North-East. This finding holds also after controlling for the endogeneity of individual's schooling, which causes a decrease of the unexplained component. Reis and Crespo (2005) prove how racial wage differentials are not constant over time, as claimed by previous studies. They decompose the unexplained component into age, period and cohort effect and demonstrate that racial wage gaps are smaller for younger generations. Taking as a point of departure Campante, Crespo and Leite (2004) and Soares (2000), Guimarães (2006) adds controls for region and sector of activity, finding that unexplained differences represent 30 percent of total differentials and that non-white individuals experience higher pay gaps in the North and North-East regions.

[6] The effects of these characteristics is equal to 56.1 percent and 45.3 percent for *negros* and *mulatos,* respectively, while the so-called discrimination effect, given by differences in coefficients, is 14.6 percent for *negros* and 17.6 percent for *mulatos*.

In summary, racial wage gaps are found to be greater than gender wage gaps in recent decades (Soares, 2000). Only in periods prior to the 1980s have gender wage gaps been found to be predominant (Lovell, 1994; Lovell and Wood, 1998). Interestingly, gender wage gaps tend to be more homogenous across region than racial differentials (Calvalieri and Fernandes, 1998). Furthermore, the latter are greater in the South-East region than in the North East, and greater in urban than rural areas (Lovell, 2000; Campante, Crespo and Leite, 2004; Loureiro, Carneiro and Sachshida, 2004; Leite, 2005). Over time, gender wage gaps have noticeably decreased, while racial gaps have not. Nonetheless, work on cohorts by Reis and Crespo (2005) finds that racial wage gaps are shrinking for younger generations. When the OB decomposition is used, unexplained components generally dominate gender differentials. These findings do not hold, however, once the sample is restricted to a more homogenous occupational group, such as schoolteachers (Birdsall and Fox, 1985). Although over time gender wage gaps shrink, unexplained components tend to increase (Arabsheibani, Carneiro and Henley, 2003). For racial wage gaps, explained components are predominant—and greater—in the case of mixed-race individuals, who have higher earnings than Blacks (Arias, Yamada and Tejerina, 2004; Arcand and D'Hombres, 2004).

This paper contributes to the literature by providing estimates of the gender and ethnic wage gaps, decomposing them with an alternative to the Blinder-Oaxaca methodology. This non-parametric alternative provides two important advancements for the literature. On the one hand, it allows exploring not only the average levels of explained and unexplained wage differentials, but also the distribution of the gaps. On the other hand, it provides measures of the unexplained components of the wage gaps that are more precise, as they are freed from problems of non-overlapping supports, restricting the comparison of wages only to those individuals whose observable human capital characteristics are comparable.

3. Methodology

As mentioned above, we follow the non-parametric matching-on-characteristics technique from Ñopo (2008) in order to obtain our main decomposition estimates. This method emphasizes gender and racial differences in the supports of the distributions of observable characteristics and provides insights into the distribution of unexplained gender differences. The traditional Oaxaca-Blinder (OB) approach based on linear regressions suffers from a potential problem of misspecification due to differences in the supports of the empirical distributions of individual characteristics for females and males (gender differences in the supports). This is due to the fact that there are combinations of individual characteristics for which it is possible to find males in the labor force, but not females (or altenatively, whites but not ethnic minorities), such as males who are in their early thirties, married, and hold at least a college degree. There are also combinations of characteristics for which it is possible to find females, but not males—for example, single females who are migrants, in their late forties, and have less than an elementary school education. With such combinations of characteristics, one cannot compare outcomes across genders. By not considering this restriction, the OB decomposition is implicitly based on an "out-of-support assumption": it becomes necessary to assume that the linear estimators are also valid out of the supports of individual characteristics for which they were estimated. Ñopo (2008) then proposes a nonparametric alternative to the OB decomposition that divides the gender gap (of any other outcome of interest, such as earnings) into four additive elements:

$$\Delta=(\Delta_X+\Delta_F+\Delta_M)+\Delta_0$$

where

Δ_X : part accounted by differences between the distributions of males' and females' individual characteristics over their common support.

Δ_F : due to the existence of some combinations of females' characteristics that are not comparable to those of males.

Δ_M : due to the existence of some combinations of males' characteristics that are not comparable to those of females.

Δ_0 : part that cannot be explained by differences in observable individual characteristics.

The first three components can be attributed to the existence of differences in individuals' characteristics that the labor market rewards, while the last one is due to the existence of a combination of both unobservable (by the econometrician) differences in characteristics that the labor market rewards and discrimination.

Along with the misspecification problem associated with gender and racial differences in the supports, the OB decomposition is only informative about the average unexplained difference in wages. It is therefore not capable of addressing the distribution of these unexplained differences. The matching technique enables us to highlight the problem of gender differences in the supports and also to provide information about the distribution of the unexplained pay differences. It estimates the four components by re-sampling all females without replacement and matches each observation to one synthetic male, obtained averaging the characteristics of all males with exactly the same characteristics. The matching algorithm in its basic form can be summarized as follows:

- Step 1: Select one female from the sample (without replacement).
- Step 2: Select all the males that have the same characteristics as the female previously selected.
- Step 3: With all the individuals selected in Step 2, construct a synthetic individual whose characteristics are equal to the average of all of them and "match" him to the original female.
- Step 4: Put the observations of both individuals (the synthetic male and the female) in their respective new samples of matched individuals.
- Repeat the steps 1 through 4 until it exhausts the original female sample.

As a result of the application of this one-to-many-with-zero-discrepancies matching the dataset is partitioned. The new dataset contains observations of "matched females", "matched males", "unmatched females" and "unmatched males" so that the sets of matched males and females have the same empirical distributions of probabilities for the selected characteristics.

The purpose of re-sampling without replacement from the sample of females and with replacement from the sample of males is to preserve the empirical distribution of characteristics for females (being the case that the support for that distribution is finite). This allows us to generate the appropriate counterfactual and interpret the four components as we do in this paper. Additionally, it allows the exploration of the distribution of the unexplained differences in pay, and not only averages as in the traditional approach. For technical details on the comparability of these estimators with those of the traditional OB decomposition, as well as on the asymptotic consistency of the estimators, see Ñopo (2008).

4. Data and Empirical Findings

We use data from the national household survey for Brazil, the *Pesquisa Nacional por Amostra de Domicilios* (PNAD), covering the period from 1996 to 2006, with the sole exception of 2000 because the census was conducted in that year. The PNAD, produced and distributed by the national statistical office (the *Instituto de Geografia e Estatística,* IBGE), contains a nationally representative sample of households that is nationally representative. That sample is selected annually following a three-level multi-stage sampling procedure. We restrict our attention to workers aged between 15 and 65 and recording non-zero wages living in both urban and rural areas. The number of observations for each year of the sample is presented in Table 2.

The variable of analysis is hourly wages at the primary occupation. They are obtained from the survey by using information on monthly wages and number of hour worked per month. Then, for each wage gap decomposition wages are re-scaled such that the average wages of females (or non-white people) are normalized to one. The re-scaling facilitates the computation, but obviously it does not alter the decomposition results.

The gender variable from the survey requires no explanation, the racial one does. We use information from the question "The color or race of… is: White, Black, Asian, Brown or Indigenous?"[7] Based on that we classify individuals into two groups: white skin color and non-white skin color (which includes Black, brown and indigenous people). Asians and non-identified ethnic minorities have been dropped due to their negligible sample size.

The matching was done considering six different combinations of human capital and labor market characteristics (shown in Table 3). The first set only takes the number of years of schooling approved. The second set considers age and education, while the third one adds the region of living.[8] After these first three sets, variables referred to the labor market are added: the fourth adds type of occupations, the fifth adds the type of sectors, namely economic activities, and the sixth set adds a variable that identifies whether the individual is working in the formal sector or not. The sequence in which extra variables were added to the set of controlling

[7] "A cor ou raça do(a) e': Branca, Preta, Amarela, Parda ou Indígena."

[8] The Brazilian regions are North (Rondônia, Acre, Amazonas, Roraima, Parà, Amapà, Tocantins), North-East (Maranhão, Piauì, Cearà. Rio Grande do Norte, Paraiba, Pernambuco, Alagoas, Sergipe, Bahia), South-East (Minas Gerais, Espìrito Santo, Rio de Janeiro, São Paulo), South (Paraná, Santa Catarina, Rio Grande do Sul) and Central-West (Mato Grasso do Sul, Mato Grosso, Goiás, Distrito Federal).

characteristics has been chosen in order to leave to the last sets those variables that may end up being endogenous in a model of wage determination *à la* Mincer.

The types of occupation are ordered specifically by occupational levels: professionals, directors and managers, administrative and intermediate-level personnel, trade and commerce workers, social and personal services workers, farmers, and blue collars. Economic activities are grouped as follows: agriculture, mining, manufacturing, energy resources sector, construction, trade and tourism, transport, financial sector, and the social and personal services sector; we excluded the armed forces and non-identified sectors from the analysis. Finally, the formal sector is identified by the possession of a working card, commonly referred as *carteira de trabalho*.

As mentioned in the previous section, the matching approach helps the analysis in terms of comparable and non-comparable individuals, through the so-called overlapping supports of the distributions of observable characteristics. Along those lines, the higher the number of characteristics used, the lower the chances of finding exact matches (generally called "the curse of dimensionality" of non-parametric methods). On the other hand, a researcher would like to control for the most comprehensive set of observable characteristics possible. This highlights the trade-off that exists regarding the number of control characteristics to use and the size of the non-overlapping supports. Figures 1.a and 1.b illustrate the percentages of men and women, for gender gap, and of white and non-white individuals, for racial gap, that are in the common support for each set of characteristics.

It is straightforward to notice that the more variables are added to the control set, the lower the percentage of individuals in the common support. By gender, we find that a range from 30.8 percent to 58.84 percent of men were found to not match with women and from 28.9 percent to 40.3 percent of women that do not match with any men. By race, the range is from 33.1 percent to 46.7 percent of whites and from 27.42 percent to 33.1 percent of non-whites. From both figures we can also see that labor market characteristics (that is, in the jump from set IV to set VI: occupation, economic sector and formality) shrink the ratios of individuals in the common support considerably more than other more personal variables do.

Table 4.a. presents average characteristics of the compared individual in and out of the common supports. There are significant differences in characteristics across male and female individuals that are in and out the common support. In terms of age, the pattern seems to be homogeneous, although unmatched individuals are likely to be older. From the distribution of the

years of education across unmatched and matched people, it emerges that unmatched women are on average better educated than unmatched men over time. Some 9.16 percent of unmatched women have attained more than 15 years of education, compared to 6.15 percent of unmatched men in 1996, while in 2006 these percentages increase to 16.56 percent for unmatched women and 7.59 percent for unmatched men. Looking at other personal characteristics, men who do not seem to match with female individuals are more likely to be non-white and to live in rural areas. From the distribution of individuals across regions, we find regional homogeneity in and out of the common support, with the South-East and the North-East showing the highest densities.

Labor characteristics provide interesting differences by gender: looking at the occupational level, in 1996 77.26 percent of unmatched women work at the intermediate level and 14 percent as professionals, while 67.46 percent of unmatched men are blue collars and only 5.21 percent are professionals. Over time, the number of unmatched individuals working as professional increases, up to 22.68 percent for women and 17.45 percent for men. In addition, unmatched men are more likely to be employed in the informal sector. Unmatched men are more concentrated in economic activities such as agriculture and construction, while 70.96 percent of unmatched women are employed in social services.

Table 4.b. provides information on characteristics for matched and unmatched people by race. As in the case of gender, age tends to be homogeneous across persons in and out of the common support and over time. In terms of years of education, 19.91 percent of white people who do not match with any non-whites possess more than 15 years of schooling in 1996 and 28.29 percent in 2006, compared with 2.80 percent in 1996 and 5.35 percent in 2006 for unmatched non-whites. Furthermore, unmatched non-whites are more likely to be men. The geographical distribution of in and out of support individuals is very interesting: there seems to be a geographical concentration of unmatched non-whites in the North-East and of unmatched whites in the South. This pattern reflects Brazilian regional disparities by racial groups.

Reflecting educational attainments patterns, unmatched whites are more likely to be professionals, reaching 38.16 percent in 2006. In contrast, unmatched non-whites are mainly employed as blue collars and more likely to be in the informal sector. Racial differences in and out of the common support in term of economic activities are in general less pronounced than gender differences, although unmatched non-white people are more likely to work in sectors with a higher density of low-skilled workers, such as agriculture and construction.

As presented in the previous methodological section, wage gaps are decomposed into the four components for each of the six combinations of characteristics and over time. The wage gap is defined as the difference in relative wages, which are constructed as multiples of average female wages for gender wage gaps analysis, or non-white wages for racial wage gaps. Hence for all graphs plotting the wage gap decomposition, each histogram represents the total wage gap for a specific year and each of the four components is proportionally detected.

Figure 2.a. reports the gender wage gaps decomposition. Total gender wage gaps shrink by 25 percent, from 0.522 in 1996 to 0.391 in 2006. The dominance of the unexplained component is striking: the main portion of gender wage gaps is unexplained even when we control for a set of characteristics. In fact, when we controlled for the more comprehensive set of characteristics, the Δ_0 is 127 percent of the total wage gap. The explained component given by Δ_X is always negative for wage differentials by gender. This negative sign of the differences in characteristics is explained by women's relatively better endowments, particularly in terms of educational achievement, a finding is in line with the literature as illustrated in Section 2.

It is interesting to note that even though the total gender wage gap has decreased over time, this change has resulted mainly from the considerable decrease in explained differences rather than a drop in the unexplained component. The portion of the wage gap that is attributable to unmatched individuals is negligible. In particular, the minute size of the Δ_M highlights the limited extent of men's privileges.

The decomposition provided in Figure 2.b. refers to racial wage gaps, which display a very different pattern than gender wage gaps. The racial wage gap is not only greater, but it has also decreased more slowly. Starting from a value of 0.961 in 1996, it shrinks by 18 percent to 0.787 in 2006. In contrast to the gender wage gap decomposition, the unexplained component tends to be small: after controlling for the wider set of characteristics, Δ_0 accounts for approximately 18 percent of the total gap. The main share is given by the explained component Δ_X. Although the explained component is the predominant term of racial gaps, it is less responsible for the decrease in the total gap: the unexplained component has decreased by 15.2 percent from 1996 to 2006.

Looking at the components that correspond to the unmatched individuals, we find a negative Δ_{NW} that represents the portion of differentials for which there are non-whites that cannot be matched with whites. Interestingly, the portion of Δ_W, for which we find whites that do not match with non-white individuals explains more than the Δ_X and is fairly stable over time. This feature can be justified by the extent of a consistent portion of white workers that are better off in terms of human capital characteristics and may ultimately hold CEO positions.

The analysis of earnings differentials and their decomposition may be more informative when the entire distribution is considered and not only mean values. By analyzing at the extent of explained and unexplained wage gaps for different individual characteristics, we are able to identify which sub-groups of population are more likely to suffer sharper differentials in earnings. Tables 5.a. and 5.b. report gender and racial wage gaps, respectively, by different characteristic, considering only the first year (1996) and the last year (2006) of the period under study.[9]

As shown in Table 5.a., wage gaps increase with age, becoming greater at higher levels of education and, consequently, for top job positions. The gap for the youngest age group is notoriously smaller than the rest. This may be explained by the fact that at these ages many individuals are still at school and hence selection into the labor markets plays an important role, it is interesting to note that in the construction sector females tend to earn higher wages and hence the gaps are negative. As already shown in the case of gender gaps, the unexplained component is greater than the total wage gap for the majority of sub-groups considered. In a few cases, again for higher levels of education and job position, the Δ_0 is smaller than the total differential. In these cases the number of out of support individuals tends to be greater, and the wage gap is largely explained by wage gap is explained by differences in characteristics in and out of the support. The gender wage gaps are greater among white than non-white individuals and in urban regions than in the national averages. Geographically, the gaps are also higher in the South and Southeast.

Table 5.b. shows a similar pattern of racial wage gaps at higher levels of education and job occupation. Furthermore, age seems to matter more in the case of racial than gender differentials: more aged individuals suffer by greater wage differentials mainly if they are non-white. Finally, the distribution of racial wage gaps by geographical region confirms once again the crucial role played by this variable in terms of racial differentials. Racial wage gaps are bigger in the Southeast.

[9] We report only the results for the first and last year since the trend over the decade is fairly stable and smoothly decreasing. For all sub-samples of population, both explained and unexplained wage gaps decrease over time.

The analysis is further enriched by considering unexplained wage differentials in individual income. For this result we pooled the data sets, using the expansion factor of each year-survey and re-scaling wages such that average female wages are normalized to one in each year. In this way we abstract from time changes of wages for the overall economy and focus on wage gaps. Then, at each percentile of the wages distribution of males and females (whites and non-whites) respectively, we compare the wages of the representative individuals in each distribution and compute the wage gap between these two. The results are shown in Figures 3a and 3b.

Figure 3.a reports the entire distribution for both total and unexplained relative gender wage gaps, after controlling for the richer set of observable characteristics. The relative gender wage gap shows a U-shape when drawn by percentile, particularly in the case of the unexplained wage gap. Notice that the unexplained gender wage gap tends to be higher at the bottom of the distribution: low-earnings women suffer to sharper differentials. Figure 3.b presents the relative racial wage gaps. The difference between the total gap and the one that remains after controlling for the richer set of observable characteristics is noticeable. The total relative racial wage gap by percentile is increasing at the upper part of the earnings distribution. Although the unexplained racial wage gap is considerably smaller than the total, it also shows greater differentials for better-paid workers, a result similar to Crespo (2003).

To conclude, the analysis of wage differentials by percentile confirms that in contrast to what happens with total wage gaps, the unexplained components are greater for gender than for race. In the case of the gender wage gap, lower percentiles suffer to wider differentials, while for the racial wage gap higher percentiles show greater differentials. The problem of wage gaps is more associated with a problem of poverty along the gender divide, but not for the case of racial gaps.

5. Conclusions

Summarizing, we have found that the ethnic wage gaps are notoriously larger than gender gaps, but after controlling for observable individual characteristics the situation is reversed. The unexplained components of wage gaps are smaller along the ethnic divide than along the gender divide. Also, the unexplained components have been slightly decreasing over the last decade, especially after 2002.

Observable individual characteristics play an important in role explaining wage differentials between whites and non-whites but a smaller role in gender wage gaps. Among those characteristics, education plays a prominent role, but labor markets characteristics (occupation, economic sector and formality) are also significant in explaining white vs. non-white wage differentials. The data suggest that the way in which these labor market characteristics operate takes the form of some sort of access barriers (as the Delta-W components are the highest among the four). Almost half of the white vs. non-white wage differentials can be explained by the fact that white individuals have access to certain occupations, in certain sectors and with a certain degree of formality that non-whites cannot achieve. In other words, while education matters, segregation in labor markets matters as well.

Unexplained gender and racial wage gaps increase with workers' age and education, and they are additionally higher among professionals and higher in the South-East. The unexplained gender wage gap is highest among poorer individuals and lowest among middle-income individuals, and then increases again for higher-income individuals. The unexplained racial wage gaps increases monotonically, although slightly, with income.

The policy recommendation is mixed. On the one hand, it is imperative to reduce human capital disparities among the population, especially improving those of ethnic minorities. Education is the key tool in this regard. While there have been improvements in quantity of education (enrollment, repetition, years of schooling achieved), the quality and relevance of education represent an ongoing challenge. At the same time, the data suggest the existence of important segregation and access barriers, and to address these problems educational policy has to be complemented with other actions that have more immediate effects. This is probably the margin at which the informative and demonstration effects of affirmative action policies may have a role to play.

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Tables and Figures

Table 1. Summary of the Literature

Authors and year	Data	Main Findings	Applied Methodology
Both gender and racial wage gaps			
Lovell (1994)	Census 1960, 1980: workers aged 10-64 living in urban areas	Before 1980, gender gaps were greater than racial gaps	Modified version of OB decomposition as proposed by Jones and Kelly (1984)
Lovell and Wood (1998)	Census 1960, 1980: workers aged 18-64 living in urban areas.	Over time, unexplained component increases while explained one decreases	Modified version of OB decomposition as proposed by Jones and Kelly (1984)
Soares (2000)	PNAD 1987-1998	In 1998, racial wage gaps are greater than gender ones Racial gaps are constant, while gender gaps decrease over time Explained component is predominant in racial gaps while unexplained one is dominant in gender gaps	OB decomposition
Lovell (2000)	Census 1980, 1991: workers living in metropolitan areas of Sao Paulo and Bahia	Wage gaps are greater in Sao Paulo than in Bahia	Modified version of OB decomposition as proposed by Jones and Kelly (1984)
Crespo (2003)	PNAD 1996	Similar to Soares (2000)	Bourguignon, Ferreira and Leite (2002)
Carvalho, Neri and Silva (2006)	PNAD 2003	After controlling for selectivity bias, the unexplained component shrinks	OB decomposition with correction for selection bias (participation in the labor market)
Lovell (2006)	Census 1960, 1980, 1991 and 2000: workers aged 18-64 living in metropolitan area of Sao Paulo	Restricting the analysis only at Sao Paulo, both racial and gender wage gaps show the dominance of the unexplained component	Modified version of OB decomposition as proposed by Jones and Kelly (1984)

Table 1., continued

Gender wage gap			
Birdsall and Fox (1985)	Census 1970: schoolteachers	Restricting the analysis only to schoolteachers, the explained component is greater than the unexplained one	OB decomposition
Stelcner et al. (1992)	Census 1980	The explained component is negative due to characteristics that favor women The unexplained component dramatically decreases in computing gender gaps among single and young individuals	OB decomposition with correction for selection bias (participation in the labor market)
Tiefenthaler (1992)	PNAD 1989	Gender wage gap is greater in the formal market than in the informal one The unexplained component follows the same pattern	OB decomposition with correction for selection bias MNL estimation for formal, informal and self-employed sectors for estimating the participation into labor market
Ometto, Hoffmann and Avles (1999)	PNAD 1981-1990: workers living in urban areas of São Paulo and Pernanbuco	Whilst in São Paulo gender wage gap is explained by inter- and intra-occupations discrimination, in Pernanbuco only intra-occupations discrimination plays a relevant role.	OB decomposition following the re-formulation developed by Brown et al (1980)
Leme and Wajinman (2000)	PNAD 1988-1997: workers aged 25-35 years	Returns to education started to benefit women that were born after the fifties	OB decomposition by cohorts
Arabsheibani, Carneiro and Henley (2003)	PNAD 1988-1998	Gender wage gap decreases over time but with an increasing unexplained component	Juhn, Murphy and Pierce's (1993) version of OB decomposition
Loureiro, Carneiro and Sachshida (2004)	PNAD 1992, 1998	Gender wage gaps are greater in urban areas than in rural ones The unexplained component follows the same pattern	OB decomposition with correction for selection bias (participation in the labor market)

Table 1, continued

Racial wage gap			
Silva (1980)	Census 1960: male workers living in the metropolitan areas of Rio de Janeiro	For racial wage gaps, explained component dominates Black and brown people show similar pattern	OB decomposition
Arias, Yamada and Tejerina (2004)	PNAD 1996: male workers aged 15-65 living in urban areas	Brown people at the bottom of the earning distribution are similar to black individuals, while browns at the top are similar to whites	OB decomposition with quantile regression (Koenker and Bassett, 1978)
Arcand and D'Hombres (2004)	PNAD 1998: male workers aged 15-65	Unexplained component is greater in the case of black people than brown individuals The impact of occupational segregation is negligible	OB decomposition with quantile regression (Koenker and Bassett, 1978) and correction for selection bias for occupational attachment (Brown et al, 1980)
Campante, Crespo and Leite (2004)	PNAD 1996: workers living in urban areas of the North East and the South East regions	In the South-East the wage gap is greater as well as the unexplained component	Juhn, Murphy and Pierce's (1993) version of OB decomposition
Reis and Crespo (2005)	PNAD 1987, 1990, 1993, 1996, 1999, 2002: male workers aged 21-65 living in urban areas	Wage differentials are shrinking for younger generations	OB decomposition
Leite (2005)	PNAD 1996: male workers aged 25-45	The unexplained component is higher in the South-East and lower in the North-East with respect to the national average	OB decomposition and 2SLS methods to control for endogeneity of individual's schooling)
Guimarães (2006)	PNAD 2002: male and female urban workers aged 10 or above	The unexplained component is smaller than the explained one and wage differentials are higher in the North-East with respect to the national average	OB decomposition

Source: Authors' compilation.

Table 2. Sample Size, 1996-2006

	1996	1997	1998	1999	2001	2002	2003	2004	2005	2006
Women	44,688	46,875	47,020	48,848	53,628	56,200	56,260	60,477	62,592	64,553
Men	72,404	77,178	75,632	77,173	82,750	84,553	84,199	88,736	91,545	92,997
Non-Whites	53,279	57,529	57,066	58,619	65,602	68,609	69,708	75,059	79,826	81,872
Whites	63,813	66,524	65,586	67,402	70,776	72,144	70,751	74,154	74,311	75,678
Total sample	117,092	124,053	122,652	126,021	136,378	140,753	140,459	149,213	154,137	157,550

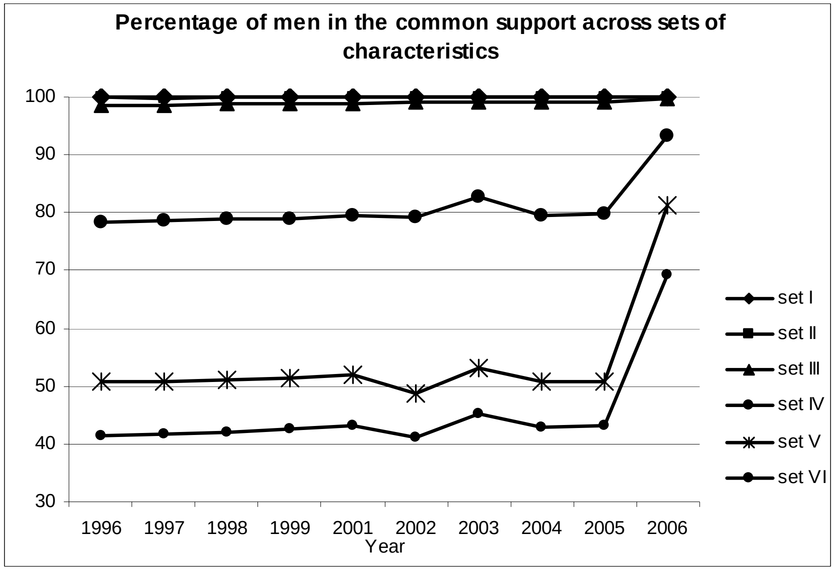
Source: Authors' compilation.

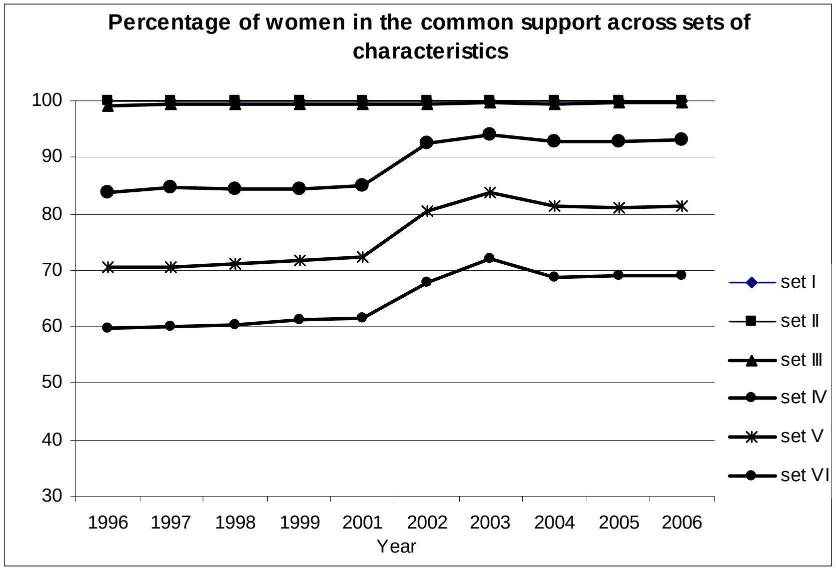
Table 3. Sets of Control Variables Considered for Matching Exercises

Type of set	**Control variables considered**
Set I	Age
Set II	Age and years of schooling
Set III	Age, years of schooling and region of residence
Set IV	Age, years of schooling, region of residence and occupation
Set V	Age, years of schooling, region of residence, occupation and economic sector
Set VI	Age, years of schooling, region of residence, occupation, economic sector and formality

Source: Authors' compilation.

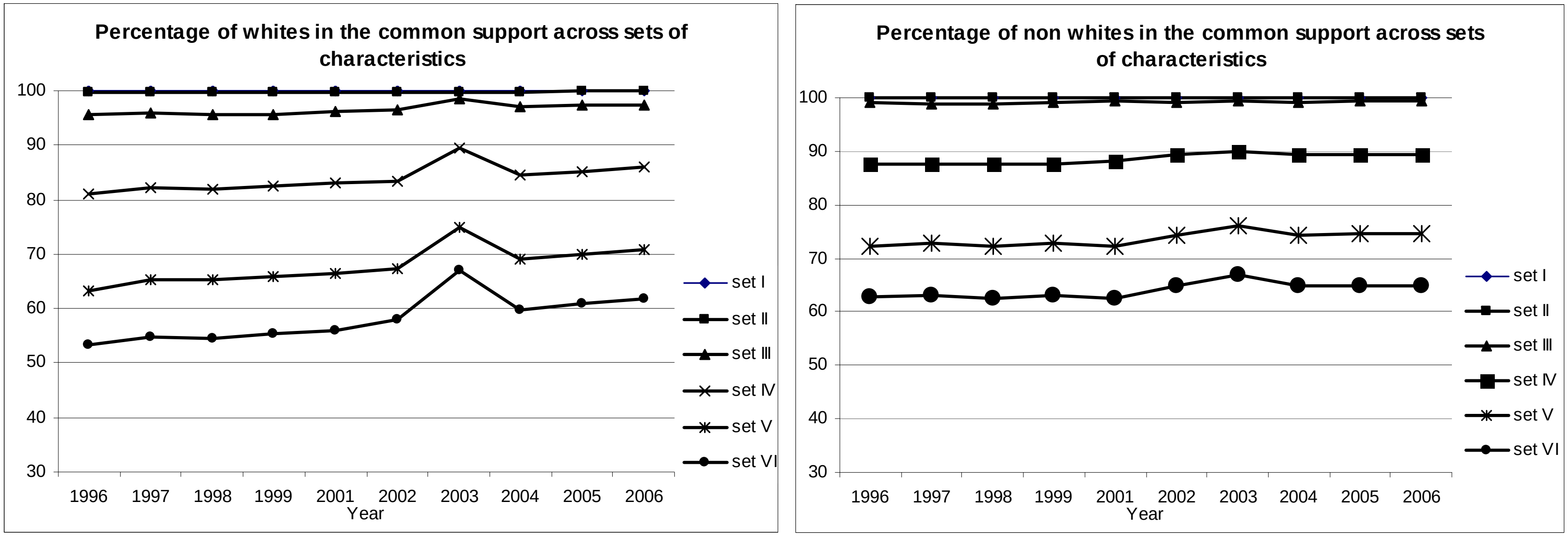
Figure 1.a. Percentages of Men and Women Matched by Different Control Sets





Source: Authors' calculations based on PNAD 1996-2006.

Figure 1.b. Percentages of White and Non-White Individuals Matched by Different Control Sets



Source: Authors' calculations based on PNAD 1996-2006.

Table 4.a. Summary Statistics by Gender in and out of the Common Support Controlling for Set of Characteristics VI, 1996 and 2006 (percentages)

		1996			2006		
		Unmatched Females	Unmatched Males	Matched Females and Males	Unmatched Females	Unmatched Males	Matched Females and Males
Personal characteristics							
Age groups:							
	15-24	28.22	26.62	27.17	19.70	22.43	25.93
	25-34	27.50	27.29	31.03	26.76	26.74	29.17
	35-44	24.91	23.36	24.93	26.44	24.90	24.83
	45-54	13.59	14.96	12.46	19.10	17.65	14.73
	55-65	5.78	7.76	4.41	8.00	8.27	5.34
		100	100	100	100	100	100
Years of education:							
	less than 4	28.36	33.66	27.85	19.47	25.73	19.37
	4-10	59.24	58.87	59.84	58.62	64.78	60.43
	11-15	3.25	1.32	1.21	5.36	1.90	2.53
	more than 15	9.16	6.15	11.10	16.56	7.59	17.67
		100	100	100	100	100	100
White		54.25	52.93	55.74	51.27	44.80	49.26
Urban		92.08	84.60	84.87	93.43	85.70	87.55
Regions:							
	N	10.92	9	4.09	14.9	15.29	10.28
	NE	22.4	23	32.05	21.32	25.17	31.46
	SE	29.89	33.73	40.12	25.94	28.20	33.91
	S	21.38	19.7	16.77	21.5	16.52	15.43
	CW	15.40	14.53	6.97	16.34	14.83	8.92
		100	100	100	100	100	100
Labor characteristics							
Occupational levels:							
	Professional	14.11	5.21	14.42	22.68	17.45	23.72
	Intermediate	77.26	27.34	49.62	69.2	18.99	51.49
	Blue collar	8.63	67.46	35.96	8.12	63.56	25
		100	100	100	100	100	100
Formal		45.27	44.87	50.93	42.61	43.87	52.74
Agriculture		0.71	15.62	12.98	0.97	13.73	10.17
Construction		0.60	19.80	0.25	1.19	21.82	0.24
Social services		70.96	20.21	46.49	55.4	12.98	45.4

Source: Authors' calculations based on PNAD 1996 and 2006.

Table 4.b. Summary Statistics by Race in and Out of the Common Support Controlling for Set of Characteristics VI, 1996 and 2006 (percentages)

		1996			2006		
		Unmatched Non-Whites	Unmatched Whites	Matched Non-Whites and Whites	Unmatched Non-Whites	Unmatched Whites	Matched Non-Whites and Whites
Personal characteristics							
Age groups:							
	15-24	28.92	23.21	28.34	24.02	19.22	25.34
	25-34	27.37	27.73	30.27	28.07	25.30	28.86
	35-44	23.00	24.77	24.58	23.15	24.53	25.76
	45-54	13.69	16.01	12.40	16.70	20.45	14.91
	55-65	7.01	8.28	4.41	8.06	10.50	5.13
		100	100	100	100	100	100
Years of education:							
	less than 4	39.63	19.38	31.87	29.98	13.12	21.65
	4-10	56.44	56.86	61.41	62.91	51.97	64.73
	11-15	1.12	3.85	0.74	1.76	6.62	1.75
	more than 15	2.80	19.91	5.98	5.35	28.29	11.88
		100	100	100	100	100	100
Male		70.05	64.93	58.07	69.97	63.08	54.71
Urban		87.80	90.64	83.21	87.14	92.40	86.47
Regions:							
	N	19.84	4	4.42	25.95	6.05	10.54
	NE	39.85	9.24	31.52	35.06	9.83	31.36
	SE	18.44	33.19	42.79	16.76	30.07	35.38
	S	4.42	42.52	12.09	4.88	41.98	12.57
	CW	17.46	10.82	9.19	17.35	12.06	10.16
		100	100	100	100	100	100
Labor characteristics							
Type of occupation:							
	Professionals	7.05	14.85	10.65	16.07	38.16	18.30
	Intermediate	43.33	52	44.77	41.69	35.71	45.66
	Blue collar	49.62	33.22	44.58	42.24	26.12	36.04
		100	100	100	100	100	100
Formal		49.13	51.85	45.74	47.19	50.90	48.21
Agriculture		9.4	7.25	14.93	9.12	5.97	11.72
Construction		11.05	5.59	7.08	11.03	5.51	7.1
Social services		35.21	35.84	44.55	25.27	28.04	41.22

Source: Authors' calculations based on PNAD 1996 and 2006.

Figure 2.a. Gender Wage Gaps Controlling for Different Sets of Characteristics

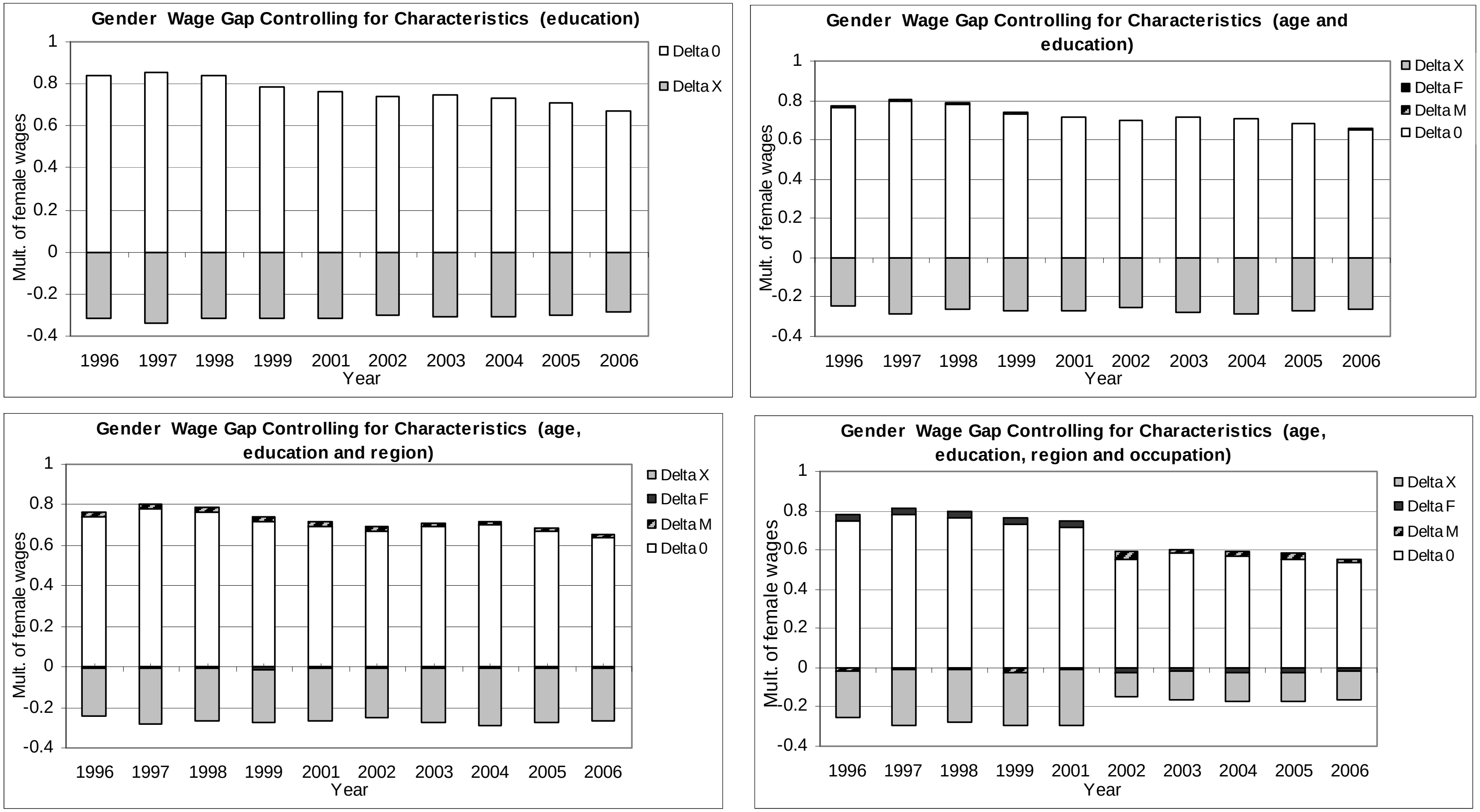


Figure 2.a., continued

Source: Authors' calculations based on PNAD 1996-2006.

Figure 2.b. Racial Wage Gaps Controlling for Different Sets of Characteristics

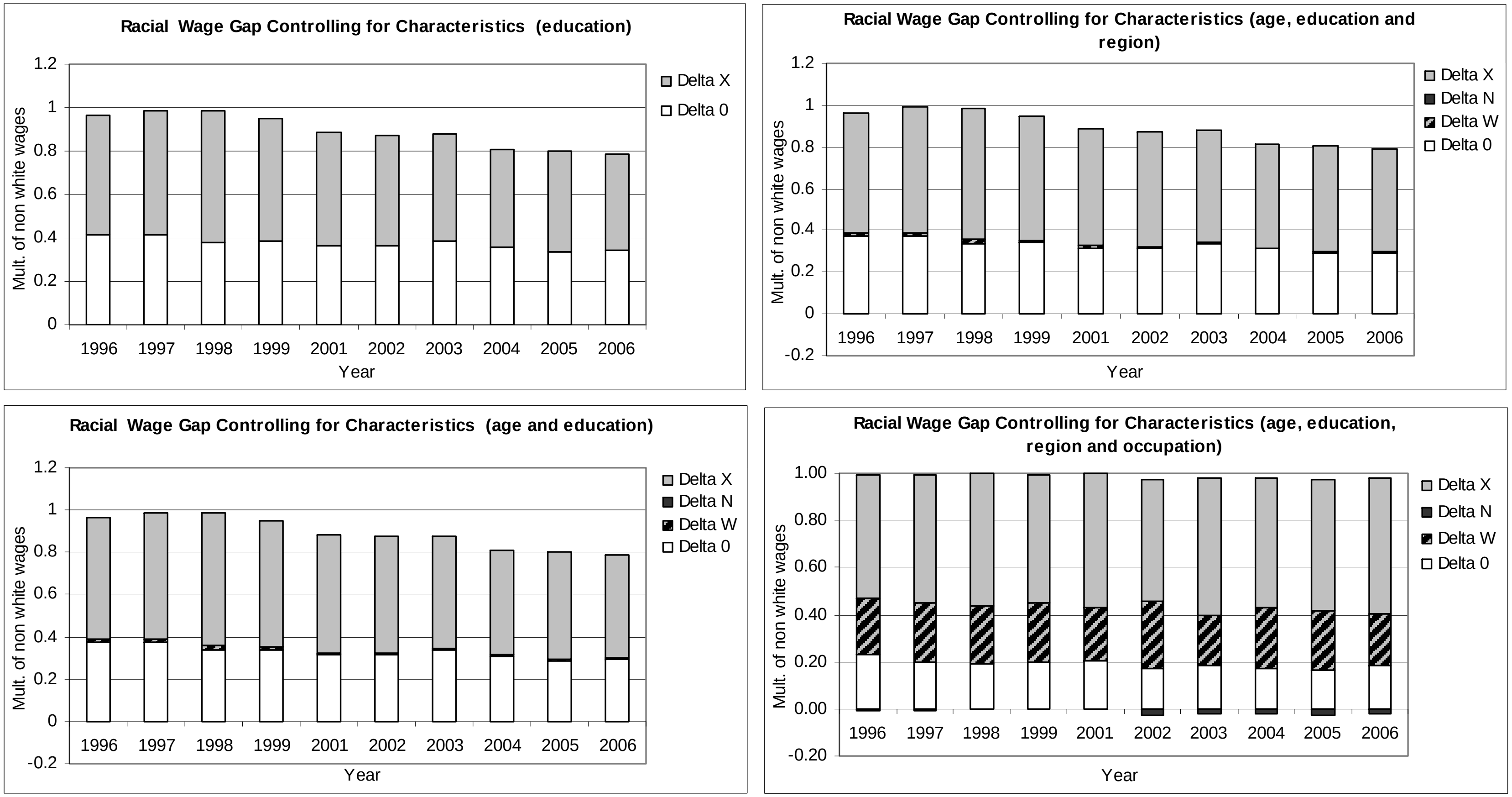
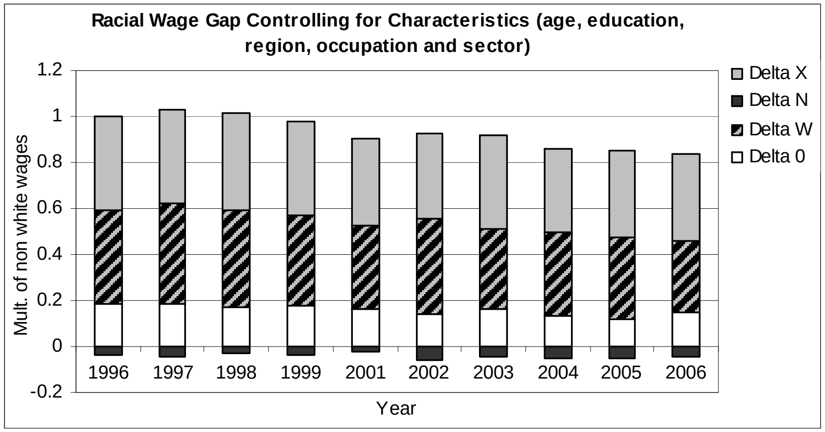
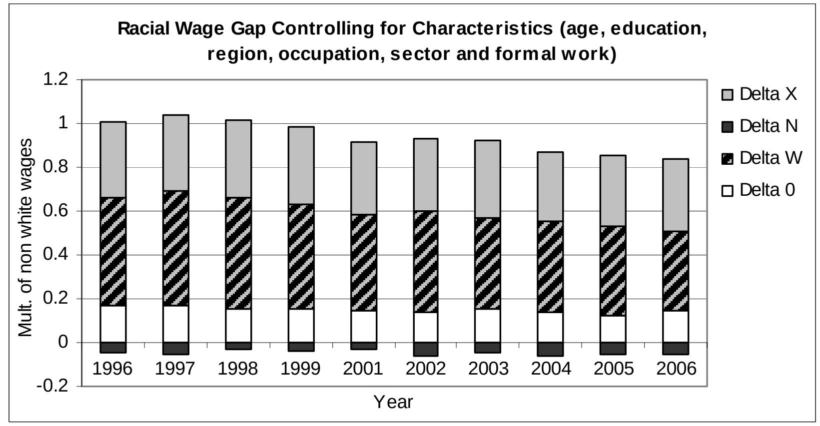


Figure 2.b., continued





Source: Authors' calculations based on PNAD 1996-2006.

Table 5.a. Total and Unexplained Gender Wage Gaps for 1996 and 2006 by Selected Characteristics, Multiples of Average Female Wages

		1996		2006	
		Δ	Δ_0	Δ	Δ_0
Personal characteristics					
Age groups:					
	15-24	0.1533	0.2228	0.1095	0.1563
	25-34	0.4443	0.6623	0.3037	0.4505
	35-44	0.7203	0.8150	0.5043	0.6662
	45-54	0.9656	0.8836	0.6693	0.8247
	55-65	0.7083	0.4820	0.6816	0.6895
Years of education:					
	less than 4	0.2742	0.2316	0.2200	0.1887
	4-10	0.5599	0.4476	0.3910	0.2875
	11-15	1.4168	1.2988	1.1831	0.6829
	more than 15	2.7695	1.4935	2.0793	1.4034
White		0.7123	0.7244	0.5761	0.6351
Urban		0.6302	0.6346	0.4734	0.5238
Regions:					
	N	0.3731	0.5028	0.2869	0.4390
	NE	0.3166	0.4456	0.2055	0.3575
	SE	0.6491	0.6786	0.5471	0.5379
	S	0.6385	0.7026	0.5315	0.6014
	CW	0.4900	0.6418	0.4168	0.6926
Labor characteristics					
Type of occupation:					
	Professionals	2.0281	0.9763	1.1996	1.0953
	Intermediate	1.3326	0.5594	0.3239	0.2766
	Blue collar	0.4010	0.4356	0.3164	0.3362
Formal		0.4157	0.6228	0.2973	0.5396
Agriculture		0.2450	0.1831	0.2396	0.2144
Construction		-0.4695	0.3113	-1.1300	-1.4590
Social services		0.9588	0.6558	0.9541	0.5841
Total		**0.5217**	**0.6000**	**0.3911**	**0.4976**

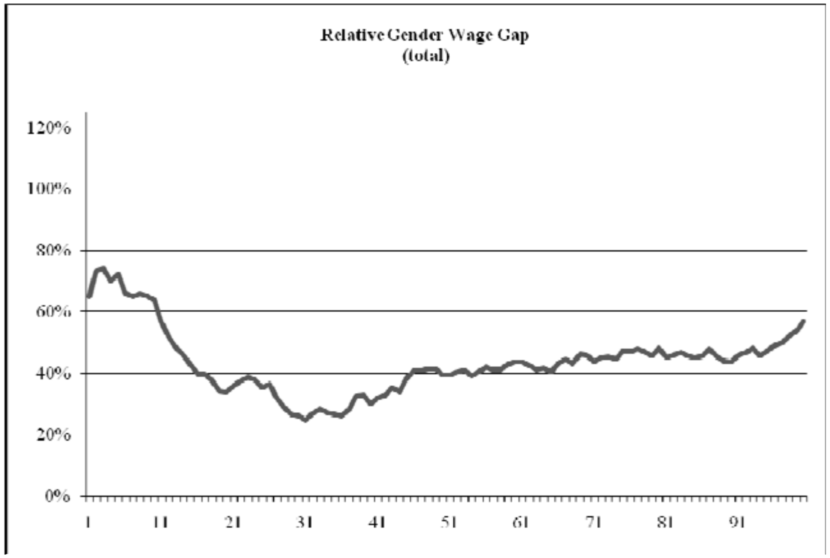
Source: Authors' calculations based on PNAD 1996-2006.

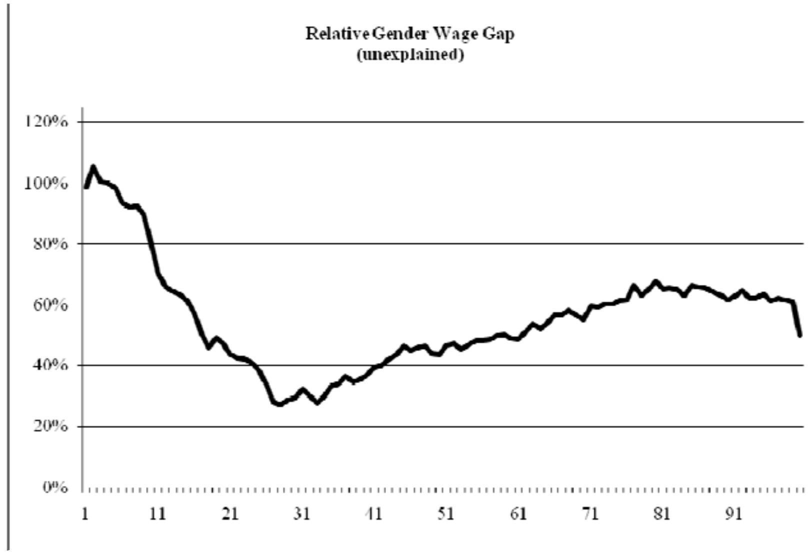
Table 5.b. Total and Unexplained Racial Wage Gaps for 1996 and 2006 by Selected Characteristics

		1996		2006	
		Δ	Δ_0	Δ	Δ_0
Personal characteristics					
Age groups:					
	15-24	0.3385	0.0826	0.2553	0.0553
	25-34	0.9131	0.2042	0.6744	0.1529
	35-44	1.2598	0.2276	0.8843	0.1505
	45-54	1.4184	0.2092	1.2105	0.2626
	55-65	1.0980	0.1223	1.2372	0.1921
Years of education:					
	less than 4	0.2638	0.0608	0.1752	0.0381
	4-10	0.4178	0.1621	0.2929	0.0847
	11-15	0.7521	0.5215	0.5473	0.3898
	more than 15	1.4609	0.6125	1.3035	0.8091
Male		1.1419	0.2022	0.9474	0.1545
Urban		0.9977	0.2028	0.8107	0.1660
Regions:					
	N	0.7186	0.0716	0.5380	0.1601
	NE	0.7450	0.0870	0.5315	0.0947
	SE	1.0691	0.2817	0.8775	0.1983
	S	0.8239	0.1787	0.7038	0.1985
	CW	0.9271	0.1636	0.8433	0.1254
Labor characteristics					
Type of occupation:					
	Professionals	1.5341	0.2392	1.3055	0.4517
	Intermediate	1.1881	0.1965	0.2948	0.0783
	Blue collar	0.4388	0.1352	0.4032	0.1106
Formal		0.8027	0.1957	0.6181	0.1493
Agriculture		0.6481	0.1084	0.6068	0.0843
Constructing		0.6448	0.1539	0.4978	0.1614
Social services		0.9919	0.1395	0.9080	0.1606
Total		**0.9613**	**0.1705**	**0.7873**	**0.1446**

Source: Authors' calculations based on PNAD 1996-2006.

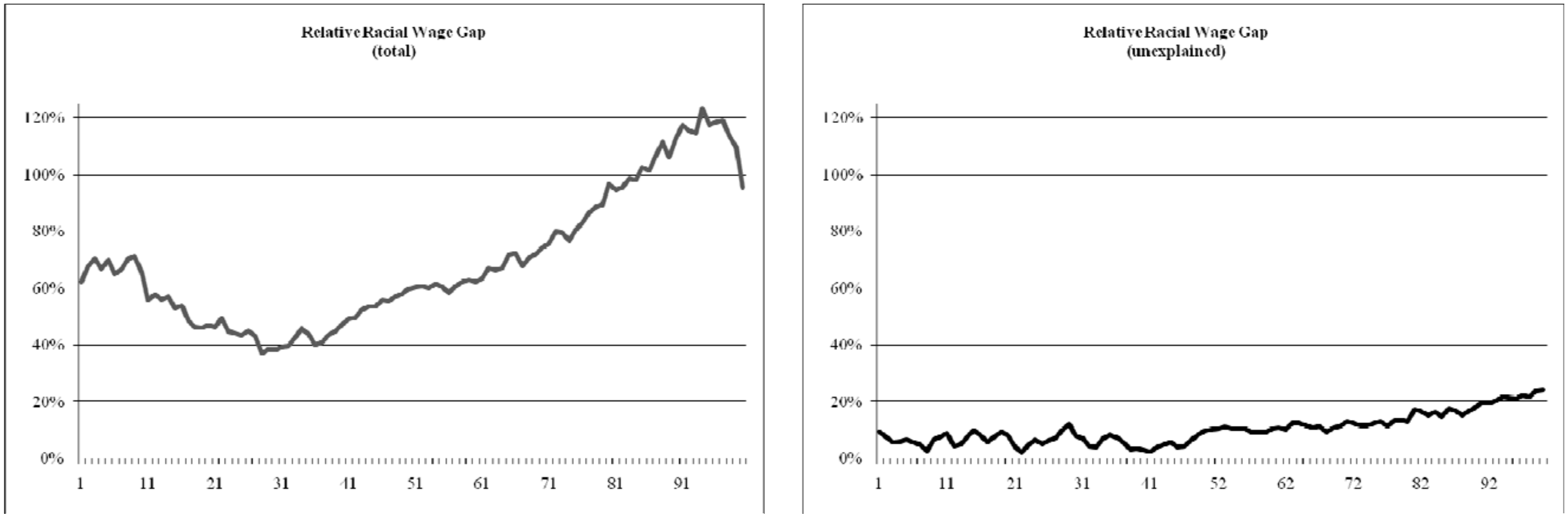
Figure 3.a. Total and Unexplained Relative Gender Wage Gap by Percentile





Source: Authors' calculations based on PNAD 1996-2006.

Figure 3.b. Total and Unexplained Relative Racial Wage Gap by Percentile



Source: Authors' calculations based on PNAD 1996-2006.