Education, Family Background and Racial Earnings Inequality in Brazil

Omar Arias, Gustavo Yamada and Luis Tejerina*

Inter-American Development Bank

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Abstract

This study combines survey data with annual state data on pupil-teacher ratios covering broadly the period 1940-90 to investigate the role of race, family background and education (both the quantity and quality) in explaining earnings inequality between whites and the African descendent population (*pretos* and *pardos*) in Brazil. We estimate quantile Mincer earnings equations to go beyond the usual racial average earnings gaps decompositions. Our main findings indicate that differences in human capital, including parental education and education quality, and in its returns, account for most but not all of the earnings gap between the African descendent population and whites. There is evidence of potential greater pay discrimination at the higher salary jobs at any given skill level. We also find that returns to education vary significantly across workers. The gradient of skin color, in itself, appears as a significant determinant of labor market performance, particularly in granting higher returns to human capital investments. While the labor market rewards the educational investments of pardos similar to those of white workers located at the top of the adjusted wage scale, pardos at the bottom are rewarded similar to pretos. Thus the common belief in Brazil that a better position in the socio-economic scale grants a fairer treatment in the labor market ("money whitens") may hold true only for pardos. The results suggest that while equalizing access to quality education, including improved early learning environments, is key to reduce inter-racial earnings inequality in Brazil, specific policies are also needed to facilitate non-whites equal access to good quality jobs.

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* The authors are Research Economist, Senior Economist, and Research Assistant at the Poverty and Inequality Unit of the Sustainable Development Department at the Inter-American Development Bank (IDB). Their views and conclusions do not necessarily represent the position of the IDB or its member countries. They would like to thank participants in seminars at the IDB, Universidad Torcuato di Tella, and LACEA 2001 for comments made on presentations of the paper. Any remaining errors are their own. Please send comments to omara@iadb.org.

1. Introduction

Social exclusion due to race or ethnicity has received increasing attention in Latin America and the Caribbean in recent years, particularly after the 2001 United Nations World Conference Against Racism held in South Africa. There is recognition of the need for better knowledge on the causes and costs of social exclusion, and the range of policies and programs for combating it. Yet most countries do not collect information on race or ethnicity regularly in household surveys or censuses. As a result, few studies analyze carefully the sources of racial inequality in the region. A notable exception is Brazil, the country with the largest population of African descent in Latin America and the Caribbean and a tradition in collecting race and ethnicity data.

In a recent survey, Silva (1999) distinguishes two main hypotheses in the classical racial relations literature in Brazil, both undermining the role of race as a relevant factor in explaining differences in socio-economic status. The "assimilation" hypothesis states that discrimination is exercised based on an individual's socio-economic class, and race (skin color, in Brazilian terms) is not a factor hindering social mobility. Thus, gaps in socio-economic achievement between whites and the population of African descend are a legacy of slavery that will eventually disappear with equitable human capital accumulation. The second hypothesis, while does not negate the distinctive role of race, poses the existence of a racial "escape hatch" by which *pardos* (mixed race) have more mobility opportunities than *pretos* (blacks). As a result, it is argued, the significant interracial marriage process in Brazil softens racial tensions; a key distinction with the U.S. racial relations system.

Empirical work following the labor economics literature on discrimination by Silva and others using 1970-80s census and survey data challenged these hypotheses. These studies find evidence of a significant labor market disadvantage unrelated to observed skills for both pardos and pretos which is attributed to discrimination. Recently, public officials in the country are publicly taking up racial exclusion as a major impediment for development, and the need for major remedies.[1]

This study aims to generate greater knowledge on the sources of racial earnings inequality in Brazil, in particular the role played by race, family background, differences in education (both

[1] For example, Paulo Renato Souza, Minister of Education, recently wrote, "...more than two-thirds of our poor and extremely poor population are afro-descendent. Our poverty, therefore, has color. And a name: exclusion." Folha de Sao Paulo, 10/24/2000.

the quantity and quality) and heterogeneity in the earnings returns to these characteristics. We examine two main questions: 1) How important are "unexplained" racial gaps in earnings and in the returns to education once we account for differences in measured productive characteristics of workers and jobs, including family background and education quality, 2) How do the gaps in earnings and returns vary for workers at different points of the adjusted earnings distribution i.e., in the lower pay and better pay jobs within any given skill level?.

To this aim, we combine household survey data on race, parental education and migration status of urban male workers for 1996 with annual state administrative data on pupil-teacher ratios covering broadly the period 1940-80s. We estimate quantile Mincer earnings regressions to account for racial earnings differentials between workers at various points of the conditional earnings distribution, and not just for average earning gaps. Moreover, we use cross-state and inter-cohort variation in pupil-teacher ratios to identify the impact of education quality on the returns to education and approximate the fraction of the racial gaps in education returns due to differences in education quality across race groups.

Our main findings indicate that while differences in human capital, including parental education, and in its returns, account for the disadvantage of non-whites with respect to whites in the lower paying jobs given measured skills, a 10 percent earnings gap remains in the top of the adjusted wage scale. Moreover, pretos face a bigger disadvantage in the returns to their education at the higher quantiles of the conditional earnings distribution than at the lower quantiles while the opposite is true for pardos. The fact that whites attend school in states with relatively better quality accounts for about half of their residual gap in returns to education. Our estimated "unexplained" gaps in the level of earnings and in returns to education imply earnings about 16% lower, on average, than granted by measured productivity differences for a typical non-white worker with a secondary education, and a 18% earnings disadvantage for non-whites with an university degree. These earnings gaps may be larger for non-white workers at the higher pay jobs within each observed level of skill.

The results indicate that equalizing access to quality education, including adequate early learning environments, is the main means to combat labor market exclusion of Brazilians of African descend. However, they also indicate that the gradient of skin color plays a role in determining labor market performance in Brazil, particularly in the higher-paying jobs of a given skill level which needs to be addressed with specific policies to combat discrimination.

The paper is organized as follows. Section 2 outlines briefly the methodology and summarizes the main relevant results from previous studies. Section 3 describes the data. Section 4 discusses the results and Section 5 concludes and outlines some policy implications.

2. Methodology and Previous Work

The traditional analysis of racial earnings inequality relies on the Mincer regression model:

$$Ln\left(w_{i,j}\right) = \alpha_j + \beta_j \, e_{i,j} + \theta_j \, X_{i,j} + \varepsilon_{i,j} \qquad \text{(i)}$$

where *w* is the wage of individual *i* of race *j*, *e* is his education level, *X* is a matrix that includes linear and quadratic terms for work experience and possibly other individual and job characteristics, and (α,β,θ) are the respective coefficients. Following Oaxaca (1973) and Blinder (1973), least squares regression is often used to decompose the racial gap in *average* wages into a component due to differences in measured productive characteristics (*e*, *X*) across racial groups and a "residual" arising from differences in how the labor market rewards such characteristics. This residual is often interpreted as a measure of discrimination. Of particular interest are the differences in the level of earnings adjusted by *X* (the intercepts αs) and in the education slope coefficients (the average returns to education βs). Silva (1999) reviews the racial discrimination literature in this tradition for Brazil. For example, based on earlier work using 1976 household survey data, he argued that around 33% and 26% of the earnings advantage of whites over pardos and pretos, respectively, could be attributed to discrimination. Lovell (1989, 1994) found similar results with 1980 census data controlling for factors such as education, experience and occupation, while showing that the gaps for pardos and pretos were not statistically different.

This approach has several limitations. First, it presumes that racial gaps in average wages fully characterize the situation of non-white workers at all points of the wage scale. Recent empirical studies indicate that unobserved worker characteristics play a non-trivial role in labor market performance. In particular, returns to education are higher for workers at the upper quantiles of the conditional wage distribution[2] so that the payoff of education may depend on a worker's endowment of unobserved characteristics (e.g., Arias, Hallock and Sosa (2001)). Non-

[2] See also Pereira and Martins (2001). Heckman and Carneiro (2001) offer another account of heterogeneity in education returns.

whites most likely compare themselves to white workers with similar characteristics, both observed and unobserved (to the econometrician), to form their perceptions of discrimination. Average wage gaps may obscure the particular conditions that affect non-white workers whose unobserved characteristics place them below or above the conditional mean wage function. As Garcia et al. (2001) suggest, this may explain the mismatch between workers' reports of discrimination and traditional discrimination measures, as documented for gender wage gaps.

Furthermore, many productivity-enhancing factors are not captured by survey data and thus remain unaccounted, complicating the interpretation of the residual component (e.g., Kim and Polachek (1994)). Particularly, non-whites often receive lower quality schooling and face less stimulating learning environments owing to the lower income and education of their parents. This may leave them with a lower α and β regardless of the presence of discrimination in pay. Moreover, estimates of returns to education can be biased due to the correlation between educational attainment and unobserved wage determinants (upward bias) and due to measurement errors in education (downward bias). Indeed, the consensus of the returns to education literature in the U.S. is that equation (1) yields estimated returns that are slightly upward biased (by about 10%) (see Card (1999)). However, it is plausible that the endogeneity of education leads to a downward biased estimate of the racial gap in education returns. This could occur if the correlation of the omitted variables (e.g., parental education) with the education and earnings of workers is stronger for non-whites, and any misreporting of education is similar across race groups.[3]

The contribution of our paper is twofold. First, in assessing racial earnings inequality we estimate the gaps in earnings and education returns for workers located at various points of the earnings distribution of each racial group. Second, we adjust these gaps by proxies, albeit imperfect, of family background and education quality (described below).

[3] For example, when parental education (F) is the only relevant variable omitted from equation (1), the bias in the estimated racial gap in average returns is given by: $E\left[\hat{\beta}_w - \hat{\beta}_{nw}\right] - \left(\beta_w - \beta_{nw}\right) = \theta_w \frac{Cov_w\left(F, educ\right)}{Var_w\left(educ\right)} - \theta_{nw} \frac{Cov_{nw}\left(F, educ\right)}{Var_{nw}\left(educ\right)}$

This will be negative if the effect of parental education on individual earnings (θ) and/or the intergenerational correlation in education is higher for non-whites, and/or if education is less dispersed for non-whites. In general, the bias will depend on the relative magnitude of the partial correlations and the measurement error in education across racial groups, accounting for other regressors.

2.1 Quantile wage functions

We use quantile regression (Koenker and Bassett (1978)) to estimate earnings and return gaps between white and non-white Brazilian workers at different points of the conditional earnings distribution. Just as least squares gives a model for the mean of the distribution of the dependent variable *Y* conditional on the regressors *Z*, quantile regressions give models for different percentiles of this distribution.[4] The τ-th quantile of *Y* conditional on *Z* is given by:

$$Q_\tau\left(Y_i \middle| Z_i\right) = Z_i' \beta(\tau) \qquad \text{(ii)}$$

where β(τ) is the slope of the quantile line and thus gives the effect of changes in Z on the τ-th conditional quantile of *Y*.[5] The partition of the regression residuals is such that at least a τ proportion are below the estimated regression line and approximately a (1-τ) fraction are above it. For instance, median regression (τ = 0.5) leaves about half of the residuals above and below the regression line, and gives the same results as ordinary least squares when the distribution is symmetric. Estimation for different values of τ (from 0 to1) yields regression lines for various percentiles of the conditional distribution of *Y*.

Figure 1 captures the basic intuition of our approach. We first estimate Mincer equations at different quantiles of the *conditional* earnings distributions of each race group separately. We then compute the difference in the intercepts and education coefficients between white and non-white workers located at the *same* quantile of the conditional distribution of each group. Thus, in equation (1) we examine:

$$Q_\tau\left(\ln w_w \middle| e, X\right) - Q_\tau\left(\ln w_{nw} \middle| e, X\right) = \left(\alpha_w(\tau) - \alpha_{nw}(\tau)\right) + \left(\beta_w(\tau) - \beta_{nw}(\tau)\right) e + \left(\theta_w(\tau) - \theta_{nw}(\tau)\right) X \qquad \text{(iii)}$$

For example, taking τ = 0.9, $\alpha_w(0.9) - \alpha_{nw}(0.9)$ (line A-A') gives the racial gap in the level of wages for uneducated workers at the 90th quantile of the conditional wage distribution of each group (adjusted by *e* and *X*), that is, the difference between the wage floor of the best paid 10% of uneducated whites and the wage floor for the top 10% of uneducated non-whites. Similarly, $\alpha_w(0.1) - \alpha_{nw}(0.1)$ measures the adjusted wage gap at the 10th quantile of the conditional

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[4] See Koenker and Portnoy (1997) and Buchinsky (1998) for a detailed discussion of quantile regression methods.

[5] In the case of dummy variables, the coefficient measures the difference in the log wages between a worker with the particular characteristic and an otherwise similar worker with the excluded category at the given quantile.

distributions (C-C'). Meanwhile $\beta_w(0.9)$ is the slope of the Mincer regression line fitted through the 90th conditional quantiles and gives the percentage change in the wage floor of the best paid 10% of whites (within each observed skill level) from an additional year of schooling. Thus, $\beta_w(0.9) - \beta_{nw}(0.9)$ gives the racial gap in the returns to education for workers at this quantile.

We can think of conditional quantiles as pertaining to workers with similar observed characteristics who end up at various points of the adjusted wage scale by virtue of their unobservable attributes. Thus, the bottom quantiles pertain to workers with wages lower than granted by their education, experience level and other measured wage determinants, and the upper quantiles to workers with wages higher than predicted by these observed skills. Interpreting wage regression residuals as a proxy of a worker's unobserved ability the relative positioning of workers in the conditional wage distribution can be related to differences in "ability", which may include a worker's labor market connections, family human capital, school quality, and/or spunk (Arias, Hallock and Sosa (2001)). The interplay of this unobserved heterogeneity with each regressor results in regression coefficients that vary across quantiles. In a recent study for South African males Mwabu & Schultz (1996) estimate wage quantile functions and find that for black males the returns to education tend to decline systematically over the quantiles while among white males the returns increase over the quantiles for higher education and decline for secondary schooling. They conclude that while for African males education is a substitute of ability, for white males higher education is a complement of ability (higher returns at the higher quantiles) and secondary education a substitute of ability (higher returns at the lower quantiles).

2.2 Family background

We use parental education to proxy for family factors that affect earnings and educational achievement such as home schooling, family wealth (which correlates with school quality), and family connections. Controls for parents' education should purge the estimated racial gaps in absolute and relative earnings from the effect of these factors[6]. This can also ameliorate any

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[6] A recent example of the U.S literature in this area is Altonji and Dunn (1996).

[7] The downward bias in the return coefficients can increase in so far these are identified from noisier information when we control for variables highly correlated with own schooling such as parental education.

differential ability bias in the estimated gaps in returns to education, although it is unclear the direction in which they could affect any measurement error bias in the estimated return gaps.[7]

The empirical evidence on the links between parental education, children's education and earnings in Brazil is strong. Various studies with PNAD data have found the effect of parental education on schooling attainment of Brazilian children to be quantitatively more important than the household head's income, slightly larger for mother's schooling (Barros and Lam (1996)), stronger at low schooling levels (Lam and Duryea (1999)), and more important than in South Africa and the U.S (Lam (1999)). Furthermore, Lam and Schoeni (1993) found significant independent effects of the schooling of parents on Brazilian males' wages, using the 1982 PNAD. Moreover, the estimated returns to own schooling declined by about 12% when controlling for both parents' education and by one-fourth to one-third when other family variables are controlled for possibly suggesting an upward bias in conventional mincer return estimators. These apparent biases are larger than those found for the U.S (Lam and Schoeni (1994)). Silva (1999) reports that racial gaps in average returns in Brazil disappear after including family background variables in empirical models.

2.3 Education quality

Since we lack data on education quality in the PNAD we use the cross-state and inter-cohort variation in educational input indicators to identify the impact of education quality on the returns to education and with this approximate the fraction of the racial gap in returns due to differences in quality. We employ a two-step regression approach used in previous work (Card and Krueger (1992)).[8] In the first stage, we estimate an expanded specification of equation (i):

$$Ln\left(w_{ijbcr}\right) = \alpha_c + \alpha_b + \alpha_r + \alpha_j + \left(\beta_{bcj} + \phi_{rr}\right) e_{ijbcr} + \theta_j X_{ijbcr} + \varepsilon_{ijbcr} \qquad \text{(iv)}$$

where the α*s* denote fixed effects for the workers' cohort (*c*), the state of birth (*b*) (proxying for the state of schooling) and current residence (*r*), and the worker's race and *X* includes individual characteristics (such as experience, father's education),. We estimate returns to education for whites and non-whites separately for each state and cohort (β_{bcj}) by interacting education with the state of birth and cohort dummies and allow the returns to vary by region of residence (ϕ_{rr}) to account for supply or demand effects across regional labor markets. We then estimate the second stage regression. By controlling for father's education, the state of birth and the individual's cohort we account for any differential effect of family background and early community factors on earnings, and ameliorate any ability bias in the return coefficients.[9] We also:

$$\hat{\beta}_{bcj} = \tilde{\alpha}_j + \tilde{\alpha}_c + \delta\, q_{bc} + \upsilon_{bc} \qquad \text{(v)}$$

That is, we regress the estimated rates of return by cohort and state of birth on a race dummy, cohort fixed effects and the education quality indicators (q_{bc}). The regression is weighted by the inverse sampling variance of the return coefficients estimated in the 1st stage The race dummy captures the differential return for non-whites purged of the effect measured racial differences in education quality. The coefficient δ measures the effect of quality on the average return to education at the state level. As explained in section 4.4 these coefficients can be used to approximate the fraction of the racial gap in average education returns potentially due to differences in education quality.

Behrman and Birdsall (1983, 1985) first incorporated education quality to the Mincer model using 1970 census data on young Brazilian males and the average schooling of teachers in the state of schooling as a proxy of quality. They found a significant rate of return to quality, later confirmed with 1980 census data (Behrman, Birdsall and Kaplan (1996)). In their more detailed analysis, using state-level measures of school quality in the U.S Card and Krueger (1992) found that returns were higher for workers educated in states with lower pupil-teacher ratios and higher teacher's education and pay. A reduction in the pupil-teacher ratio by ten students was associated with a 0.8 percentage point higher rate of return to schooling. Case (1999) found this effect to be twice as large for South Africa. Reed and Lam (1999) combined individual data from the 1988 PNAD with various state-level measures of school quality generated from PNAD surveys of the late 1970s. Their estimates suggested that characteristics of teachers, particularly their education level, were strong predictors of the wage returns to schooling while expenditure, relative teacher wages, repetition and homework assignment rates had little predictive power.

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[8] See also Heckman et al (1996), Reed and Lam (1999) and Case (1999).

[9] Regional differences in education quality can also bias education returns since they correlate with differences in schooling attainment.

Note that by including state of birth and residence fixed effects and region of residence interactions with education in (4), the effect of quality on the returns to education (δ) is identified from the co-variation between quality measures and the deviation of the state of birth-specific component of education returns from the regional mean return for migrants (workers educated in one state and later observed working in another region).[10] As emphasized by Heckman et al. (1996) this may bias the estimate of δ in (5) if migration decisions are correlated with expected earnings in the destination region. In a review of the Card and Krueger (1992) analysis, Heckman et al found evidence suggesting that the effects of quality on returns to education are non-robust to this assumption. Reed and Lam (1999) conduct a sensitivity analysis of the potential role of selective migration in their study for Brazil. Although they found their quality effects to be non-robust, their estimation suffered from limited variation in the school quality measures and a high degree of collinearity with other state variables. In their later review of the literature, Card and Krueger (1996) concluded with a more positive view on the evidence from their approach to measure the effect of school quality on students' subsequent earnings.

3. Data description

We use household survey data from the 1996 *Pesquisa Nacional por Amostra de Domicílios* (PNAD) and focus on the sample of male employed workers living in urban areas (excluding small owners and unpaid workers), age 15-65 (on a sample of about 57,000 workers). Most of our analysis is based a subsample of about 29,000 household heads that are asked to report the highest level of education attained by their parents. The data includes the worker's race, labor earnings, migration status, human capital variables (education, experience), labor market and job characteristics (type and sector of employment, unionization, region of residence and) and, for heads, parental education reported as one of ten categories (which we collapse in six). Hourly wages are computed from reported monthly earnings and total hours worked the previous week on the main occupation.[11] Work experience is computed from the difference between the worker's age and the age he started working.

[10] More precisely, from the specification of equation (4) it follows that the second stage state of birth returns are measured as deviations from the mean return in the region where migrants live. This adjusts for differences in regional labor markets that may affect the productivity of education.

[11] Throughout wages refer to hourly earnings in the case of self-employed workers.

Individuals self-identified as *branco* (whites, 57%), *pardo* or *preto* (non-whites, 39% and 7% respectively).[12] Most empirical studies of racial inequality in Brazil have relied on self-classification of race. An exception was Telles (1998) that used interviewer classification of race based on a 1995 national survey in Brazil and found that the estimate of white-nonwhite earnings inequality was greater with interviewer classification than with self-classification. However, given the arbitrariness involved in interviewer classification the consensus among survey specialists is that racial self-identification is to be preferred and remains the prevailing approach used in surveys and censuses.

Table 1 present means and relevant standard errors for these variables. There are significant racial differences in earnings and acquired productive characteristics. On average, pretos and pardos earn roughly 40% less than whites. Among household heads, the average wage gap is about 46% for pretos and 42% for pardos. White workers are less likely to have informal salaried jobs, work in agriculture and construction, and more likely to be unionized and live in the Southeast and South. Most importantly, they have a considerable advantage in own and family human capital. They have completed an average of 7.5 years of education compared to 5.6 for pardos and 5.2 for pretos. With enrollment in primary education almost universal since 1965, secondary enrollment remains a challenge, especially among the poor non-white population (O'Conell and Birdsall (2001)). As a result, white workers are three to four times more likely to attain higher education than non-whites[13].

There is evidence that the quality of education is also lower for non-whites. Private schools are generally better equipped with teaching resources but are mostly affordable to the wealthier segment of the population (Herran and Rodriguez (2000)). Unfortunately, we do not have data on education quality in the PNAD survey. However, there is considerable regional heterogeneity in the quality of public schools which traditionally account for the bulk of total enrollment in primary and lower secondary public schools (*Ensino Fundamental*, formely known as *Primero Grau*), although a recent large-scale education finance reform has led to increased funds allocations for the poorer states. We exploit this regional variation to construct proxies of education quality for the workers in our PNAD sample. We compute pupil-teacher ratios in

[12] The relevant population for inference is the urban employed male population, excluding the indigenous and Asian descendents who are a very small fraction of the labor force. Biases arising from self-selection into the labor force are not a big concern for men.

[13] Silva (1999) reports similar low rates of educational achievement and racial disparities for the general population.

primary and lower secondary public schools during the period 1938-1988 from administrative records on annual enrollment and number of teachers by state from the *Anuario Estatistico do Brazil*.[14] We assume that individuals attended school in the state they were born. We then assign each worker the pupil-teacher ratio of his state of birth-cohort measured as the average of the 10 years span in which his birth cohort would have attended school.[15] For example, an individual born in Sao Paulo in 1940 is assigned the average pupil-teacher ratio in public schools of that state during 1946-56. These are considered reasonable, albeit imperfect, proxies of the average quality of education received by workers (a lower number meaning higher quality). Schools with lower pupil-teacher ratios may have a better quality of classroom instruction and can devote better quality time to follow on the progress of students. The pupil/teacher ratio is also often correlated with other key inputs of the educational process such as instructional time, educational materials, and teachers' education and experience. Moreover, almost 70% of workers did not attend upper secondary school and the effects of quality accumulate over the school life.

Table 2 presents the average pupil-teacher ratios by region and cohort that result from the imputation of education quality to white and non-white workers in our sample.[16] Figure 2 illustrates the persistent disparities in school inputs between the states in the Northeast and the South. Although the relative supply of teachers has clearly improved considerably over the period, pupil-teacher ratios have been consistently lower in the South than in the Northeast (by about 20%, or 5 fewer pupils per teacher in the last three decades). At the same time, in our sample non-white workers account for 66% of all workers educated in northeastern states and for only 16% of those educated in the South. Note however that the correlation between race and our imputed quality measures is much weaker for Brazil as a whole. The racial differences in average pupil-teacher ratios in Table 2 are generally below 2. This reflects the considerable racial mix of the population especially in the Southeast where pupil-teacher ratios are close to the national average. About 42% of all white workers and 30% of non-whites in our sample were educated in the southeastern states. Thus, as a consequence of the state aggregation, our quality proxies

[14] The data is reported for grades 1-4 of school *(Ensino Primario)* until 1972 and grades 1-8 (*1ro Grau*) thereafter.
[15] The decade average minimizes the impact of noisy data in certain years. We also tried assigning the averages corresponding to the exact hypothetical period the individual would have attended primary school with qualitatively similar results. For states that were absorbed by other states or that were divided, we merged or repeated data to obtain a time series matching the current political division of Brazil. For example, in 1980 the state of Matto Grosso do Sul was created from the state of Matto Grosso, thus we assign the same data to both states before 1980.
[16] The detailed data for the twenty-seven states and five birth cohorts (1940-1980s) is available upon request.

probably overstate the actual quality of education received by non-whites as a whole and understate it for whites. As we discussed further below, using our overall estimates of the effect of quality on the returns to education we can approximate the fraction of the residual racial gaps in returns that could arise from differences in education quality between whites and non-whites.

Finally, non-whites, and particularly pretos, are caught in an inter-generational low-education trap. Above three-fourth of non-white household heads have parents with incomplete elementary education (1-4 years) compared to about three-fifth of whites (Table 1). A very small fraction of non-white male workers have university-educated mothers. Although the situation has improved for recent cohorts, mobility opportunities also differ significantly by race. Non-white workers, on average, consistently surpass the educational level achieved by their fathers only up to the 8th grade (see Figure 3). At the university level, only whites, on average, match the educational attainment of their fathers. This is consistent with the findings of Hasenbalg and Silva (1998) who showed that non-whites, and specially pretos, had fewer opportunities of upward social mobility, especially in the higher-level occupational groups, and face a higher probability of downward mobility.

4. Empirical results

We estimate four empirical models with different sets of control variables by ordinary least squares (mean) regression and at ten different quantiles (0.1 to 0.9).[17] Model 1 consists of the basic Mincer equation (X= experience, experience^2) with a race specific intercept, and model 2 allows all slope coefficients to also vary by race. Model 3 introduces job and labor market characteristics to account for the portion of the wage gap potentially associated to labor market segmentation.[18] Model 4 adds controls for parental education to model 2. We analyze the potential role of education quality in explaining the residual relative earnings gaps. We estimate separate regressions for whites, pretos and pardos and pool the observations for non-whites in the education quality analysis due to sample size considerations.

For comparability across specifications, we focus on the results for household heads with parental education data. The results for the sample of all workers without controls for parental

[17] All the estimations and tests were carried out in Stata v. 7.0 with bootstrap standard errors (150 replications).

education are qualitatively similar only that the estimated wage gaps are somewhat smaller and the gaps in returns larger.[19] Before discussing specific results it is worth noting the high explanatory power of our regressions. Our explanatory variables, including race, explain up to a 70% of the variability in mean log wages, a remarkable figure for these types of wage regressions.[20] Differences in education and work experience, and in its returns, alone account for most of this variation. We first discuss the results for parental education, followed by the estimated gaps in wage levels and returns to education, and then the education quality results.

4.1 Returns to parental education

Table 3 presents the estimated effects of parental education on sons' average wages for regressions that include the education of both parents and the father and mother separately (model 4). Parental education increases the wages of sons, in addition to its well-known positive effect on children's educational attainment. When the education of each parent enters the regressions separately, the coefficients capture the compound effect of parental education on the sons' average wages. This effect is generally similar for both parents' education among whites but is significantly higher when mother's education is used as a proxy among non-whites. The effects increase, although not monotonically, the higher the education level of the parents. The wage gains from having a parent with some elementary education are below 10%. The wage gains from having a parent with complete elementary or lower secondary schooling are not statistically different, but grow larger when the parent has upper secondary education and above. For instance, white workers whose father completed elementary school earn 19% (= $e^{.175}$-1) more than workers with the same education and work experience but with uneducated fathers, while those with a university-educated father earn about 80% (= $e^{.589}$-1) more. The larger wage gains arise from university-educated parents for whites and pardos, and from parents with upper secondary schooling for pretos. For example, for whites and pardos the wage advantage implied by a university-educated-father is twice as large as that implied by a father with upper secondary schooling.

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[18] As it is well recognized in the literature, the segmentation of non-whites to jobs in lower productivity industries, occupations or underdeveloped regions may also result from discriminatory practices in the labor market or their weak influence on the political process for the allocation of public resources.

[19] An appendix with the full least square results (including the full sample) is available upon request.

In order to measure the independent contribution of each parent's education we let both variables fight it out in the regression. Remarkably, we can identify these marginal effects despite the high degree of assortative mating in Brazil.[21] Our results are mixed. Mother's education generally yields higher wage returns than father's schooling among non-whites, except for pardos with highly educated fathers. The opposite is true for whites, particularly for workers with either low or university-educated parents. For pretos, while the marginal effects of father's education turn negligible mother's education remain very strong. The average wage gains for both pretos and pardos exceed 20% when the mother has completed elementary schooling and reaches 40% to 67% with a high-school-educated-mother, controlling for their own education and their father's.(compared to 9% and 25% for whites). The coefficients are quite precise despite the very low number of well-educated mothers among non-whites in our sample.[22]

The results for the quantile estimations using father's education to proxy for family factors (not reported) indicate that the effects over the quantiles are roughly constant.[23] Thus, parental education yields similar wage gains for all workers within each racial group that are well characterized by the above mean results.

These wages gains from parental education may reflect returns to unobserved worker productivity, including family specific human capital and school quality, and/or returns to labor market connections. Our findings of different marginal wage gains from a parent's education (controlling for the other parent) across race groups could arise from racial differences in the way parental education proxy for these factors. Mother's schooling is likely to play a more important role in the home production of human capital for the workers in our sample, specially given the low rates of female labor force participation in Brazil. Since the education of mothers is so low among non-whites, it may be taken as a stronger labor market signal of the productivity of a non-white worker and thus rewarded with a higher wage return compared to whites. Similarly, father's education tends to be more strongly correlated with family income and socio-

[20] The explanatory power is much higher for white workers in part due to their higher variance in educational attainment. For example, the R^2 in model 1 is 0.4 for whites, 0.32 for pardos and 0.3 for pretos.

[21] The correlation between parents' level of education is 0.62. More than three-fifth of household heads have parents with the same education level and less than 15% have parents whose schooling mismatches by more than one education level.

[22] Although having a university-educated mother doubles the wages of pretos, the effect is not statistically different from the high-school coefficient since only three pretos have university-educated mothers in our sample.

[23] We use father's education since the smaller sample with data on mother's education affects the reliability of quantile estimates, especially in the higher education cells for non-whites.

economic status than mother's education and this correlation is most likely higher in whites' families. Thus, father's education is plausibly a finer proxy of the quality of education and family connections available to workers for whites. This may be behind the higher wage gains implied by father's education for whites relative to non-whites.

Our results are in general consistent with those of Lam and Schoeni (1993) based on 1982 PNAD data, although they did not estimate separate effects by race. However, they found that the marginal wage gains of the first four years of father's schooling were higher than the gains for the years of schooling from elementary to university, in sharp contrast to our findings.[24] This tentatively suggests that the wage returns to parental education in Brazil during the past two decades may have also followed a pattern of convexification as documented for the returns to own schooling (Ferreira and Paes de Barros (2001)). Thus, the documented large contribution of the inequality in the distribution of education to earnings inequality in Brazil is amplified by inter-generational factors that show an important interplay with race.

4.2 Absolute earnings gaps

Figure 4 compares the wage distributions for whites, pardos and pretos (household heads).[25] The distribution for whites is further to the right reflecting their wage advantage at any wage level. On average, pretos and pardos earn about 46% and 42% less than whites, respectively. However, these averages mask substantial disparities between workers at different points of the wage scale. In fact, the distributions become further apart at the right tail. That is, racial wage gaps are larger between workers at jobs with higher pay jobs. A preto at the 0.10 quantile of the wage distribution for pretos (whose wage places him above 10% of pretos) earn about 24% less than a white worker at the 0.10 quantile of the distribution for whites (the distance between A and B). The wage gap then increases to 56% at the 0.90 quantile (the C-D distance). The wage gap for pardos is similar at the 0.10 quantile and about 50% at the 0.90 quantile. Thus, the wage floor for the best paid 10% of whites is about 2 times larger than the wage floor for the best paid 10% of non-whites compared to 1.3 times higher at the bottom 10% of the wage scale.

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[24] For example, in a comparable regression specification (Table 2, col. 2 in their paper), they found that the wage increase from having a father with complete elementary with respect to an uneducated father was 18.8% and 14.4% for a university-educated father relative to a father with 4 years of schooling. Instead, we find these gains to be 11.8% and 38.2%, respectively, for the full sample of workers. As shown in Table 2, these wage gains are only accrued by whites and pardos.

Of course, these wage gaps in part arise from racial differences in productivity-related characteristics. We would like to know what fraction of these gaps remain “unexplained” after we account such differences. As explained in section 2.1, we do this by estimating the gaps for workers at different points of the race-specific wage distributions conditioning on observed characteristics, that is, the wage distributions that would result if all workers had the same set of measured characteristics. Table 4 summarizes the unadjusted gaps (computed from the raw wage data underlying Figure 3) and the regression-adjusted wage gaps (differences in the wage regression intercepts) measured at the mean and at ten different quantiles. The column labels refer to the empirical specifications of equation 1 described before. Each coefficient measures the wages of pretos and pardos as a fraction of whites’ wages at the given point of the wage distributions. By subtracting one and comparing across columns we get the fraction of the wage gap at a given quantile (or at the mean) that remains unexplained by the regression.[26] Moving across rows from first to last, on a given column, shows the variation of the wage gap for workers from the bottom to the top of the conditional wage distributions. For example, for each R$1 of whites’ wages, pretos earn an average of 0.541 cents, and only 0.441 cents if we compare the wage floor of the best paid 10% of whites with the respective wage floor for pretos (with percentage gaps of 46% and 56% as reported above). Adjusting for differences in education and work experience between whites and pretos reduce the wage gaps so that the fractions fall to 0.753 at the mean and to 0.695 cents for the top 10% of workers within each level of education and experience.

The results indicate that the lion’s share of the racial gaps in wages in Brazil arise from the considerable racial disparities in the productive characteristics of workers and jobs. Racial disparities in education and work experience account for about one third of the wage gaps at the lower quantiles and for almost half at the top of the wage distribution. The percentage wage gaps for pretos fall to an average of 25%, ranging from 22% at the bottom to 30% at the top of the distribution, and falls to a roughly constant 23% for pardos (see columns 1 in Table 4). Racial differences in the returns to education and experience account for about half of the residual average wage gaps which fall to roughly 12% for both pretos and pardos (see column 2).

[25] The picture is similar for the full sample of workers but with somewhat larger racial gaps over the quantiles.

[26] These are computed as $\exp\left(\alpha_\tau^{nw} - \alpha_\tau^{w}\right)$ where the αs are the race-specific regression intercepts at quantile τ.

However, this hides the fact that while the gaps become negligible at the bottom quantiles they remain at up to 25% for pretos and 15% for pardos at the top of the adjusted wage scale.

In columns 3-4 we present estimates of the wage gaps in models that adjust the Mincer equation of column 2 for differences in job characteristics and father's education, respectively. The gaps in wage levels in these models are not uniquely defined since they depend on the categories excluded from the regression (e.g., the comparator industry, region, or father's education level). In general we do not find significant variations in the residual wage gaps across different types of jobs, union membership, sector or region of employment. The most striking gaps arise for workers employed in professional, financial and real estate related services, which are reported in columns 3. Even with similar observed human capital and job characteristics, whites' wages in these sectors exceed pretos' wages by roughly 32%, while remarkably pardos' disadvantage remains at about 12%.[27] Meanwhile, parental education has the effect of equalizing the residual wage gaps for both pretos and pardos and in the upper part of the conditional wage distributions. For workers whose father has no formal education, the gaps stand at a roughly constant 12% for pretos and pardos in the upper 50% better paid jobs within any skill level (see columns 4). We conclude that the residual wage gaps turn smaller for non-whites with more educated parents (see table 3).[28]

Based on these results we draw the following conclusions. Differences in the endowments and returns to own and family human capital account for most of the wage disadvantage of non-whites, particularly at the bottom of the wage scale. A moderate wage disadvantage persists for non-white workers, particularly for pretos, who cling to the jobs of relatively higher-pay conditional on observed characteristics. These findings are similar to the results of recent studies of gender and racial earnings gaps, which offer evidence supporting worker's reports of greater pay discrimination at high salary levels (Kuhn (1987)). As we show next, these results are mimicked by the pattern of racial disparities in the returns to education.

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[27] Although the quantile wage gaps in column 3 for pretos oscillate, they are not significantly different from the estimated average gap.

[28] For example, adding up the coefficients for the education of the mother and father, when both are controlled for, yields a compensating log-wage advantage for pretos and pardos of .04 to .077 at the elementary schooling level.

4.3 Returns to education

Figure 5 depicts the estimated returns to education for each race group and empirical model. It plots the return estimates (circles) and their 95% confidence intervals (dotted lines) at each quantile, together with the mean return estimate (flat solid line). Table 5 presents the estimated quantile return coefficients and the resulting racial gaps in returns. The column labels again denote the empirical specifications of equation i. Each return coefficient corresponds to the slope of a regression line as illustrated in Figure 1. For example, in column 2 the coefficient of 14.4 at the .90 quantile for whites means that the wage floor of the best paid 10% of whites, within each education and experience, level increases by 15.5% (= $e^{.144}$-1) with each additional year of schooling. From the spread of the quantile returns (the steepness of the lined up circles in Figure 5) for each racial group we can infer how the within-group inequality in wages changes across different education levels.

Education appears as a profitable investment for all workers. However, returns vary significantly along the conditional wage distribution (the solid lines often lie outside of the quantile confidence intervals in Figure 3).[29] The mean return is not representative of the effect of education on wages for all workers. As a result, the gaps in average returns give an incomplete picture of racial inequality in relative earnings in Brazil.

Education returns are significantly lower for non-whites and, consistent with studies for Brazil, the U.S., and other countries, are higher for workers at the top of the conditional wage distributions.[30] In the basic Mincer model the average return is 13.6 for whites, compared to 12.1 and 11.5 for pardos and pretos, respectively (see columns 2 in Table 5). The pattern of quantile returns also varies with the gradient of skin color. The basic Mincerian returns for whites increase from 11.6 at the bottom to 14.4 at the median and then remains essentially constant, and increase monotonically over the quantiles from 9.7 to 13.4 for pardos. Meanwhile, the returns for pretos first increase from 9.9 at the bottom to 12.5 at the middle of the distribution and then decline to 11.8 at the top. Interpreting wage residuals as capturing unobserved factors that enhance a worker's earnings potential ("ability"), these results are consistent with education

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[29] This is confirmed by formal tests of equality of quantile coefficients (Koenker and Bassett (1982)) using the bootstrap estimate of the quantile estimator covariance matrix. These results are used in the text discussion and available upon request.

being a complement to these unobserved factors, especially for workers at the bottom of the wage scale. The higher returns at the upper quantiles imply that education increases wage dispersion, that is, wage is higher among workers with higher education levels. This effect is stronger for pardos than for pretos as reflected in the steeper quantile returns in Figure 5. This means that while we find well-educated pardos in lower return jobs as often as well-educated pretos, we find well-educated pardos in higher return jobs more often.

A fraction of the estimated returns reflect differential returns to job characteristics and segmentation in the labor market, as reflected by the decline in all the return coefficients when we control for these factors (column 3). Adjusting for such differences in job characteristics increases the spread in the quantile returns for whites and pardos and reduces it for pretos. This means that within-group wage inequality is even higher among whites and pardos when we further focus on the wage variation within industry, region and type of employment. Meanwhile, as expected, returns to education decline when we adjust for parental education.[31] Controlling only for mother's education reduces average returns close to 10% for whites and pardos, and by 11% for pretos. When we only include father's education average returns fall by 12% for whites, 11% for pardos and close to 7% for pretos. This is essentially unaffected when we additionally control for mother's education. The results are strikingly consistent with the U.S. findings of a 10% upward ability bias in the estimated average return when one does not account for the joint correlation between family factors, earnings and education (Card (1999)). As indicated before, using father's education as a proxy for family background variables in the quantile models, reduces the spread in the quantile returns, particularly for whites and pardos. This is consistent with a differential ability bias in the estimated return coefficients that is larger at the upper quantiles, as has been found in other recent studies (Arias, Hallock and Sosa (2001)). The patterns of quantile returns remain intact when we control for parental education and various job characteristics.[32]

Note however that racial differences in these factors do not fully account for the observed gaps in education returns. The quantile return gaps in the basic Mincer model range from 1.7 to

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[30] See, for example, Arias, Hallock and Sosa (2001), Blom, Nielsen-Holm and Verner (2001), Machado and Mata (2001), Pereira and Martins (2000), Mwabu and Schultz (1996), Buchinsky (1994).

[31] These least square results are based on regressions for the 27,499 workers with complete mother's education data.

[32] Regressions allowing the returns to education to vary at the primary, secondary and tertiary level also yield similar increasing patterns of quantile returns. These results are not discussed here but are available upon request.

2.6 percentage points for pretos and from 1.9 to 1 percentage point for pardos from the bottom to the top quantiles. The gaps actually increase in about 0.5 to 1 percentage points over the quantiles for both pretos and pardos when we control for job characteristics, rising to around 2 percentage points for pardos and ranging from 1.5 to 3.8 percentage points for pretos. In contrast, controlling for father's education reduces the gaps in returns by an average of 1 percentage point for pretos and 0.5 percentage point for pardos. About two-fifth of the quantile return gaps for pretos and one-fifth of the gaps for pardos are explained by the lower education of their parents.[33] Thus, estimates of racial gaps in returns to education that do not account for family factors overestimate the actual disadvantage in returns faced by non-whites. However, the unexplained gaps in returns remain significant at about 1 percentage point, on average. This is in contrast with the results reported by Silva (1999) of insignificant gaps once family background is controlled for. The gaps in returns continue to be higher for pretos at the upper quantiles (around 1.6) but lower for pardos (around 1) at the top of the adjusted wage scale.

We then conclude that, regardless of the empirical model, pretos and pardos face a distinct disadvantage in education returns vis-á-vis whites depending on their position in the conditional wage distribution. While pretos face a larger gap in education returns at the upper part of the distribution than at the bottom, the opposite is true for pardos. Pretos and pardos located at the bottom of the conditional wage distribution are treated similarly in terms of the payoff to education. Meanwhile, the 20% best paid of pardos have a return advantage of about 1 percentage point over the 20% best paid of pretos, given similar observed skill levels.

Thus, the common belief in Brazil that a better position in the socio-economic scale correlates positively with a fairer labor market treatment ("money whitens") appears to hold true only for pardos.[34] This is also consistent with the classic hypothesis in the race relations literature in Brazil that interracial marriage softens racial tensions by improving mobility opportunities for blacks. The results for pretos are consistent with our previous findings for the gaps in wage

[33] The gaps in average returns are little affected by mother's education once we control for father's education. Average return gaps for pretos fall from 2.3 in the basic Mincer model to 1.7 with both parents' education included and to 1.4 with father's education alone, while it barely changes for pardos (from 1.4 to 1.1-1.2).

[34] This is also consistent with the results in Telles (1998) and Silva (1999). Telles found that, with human capital and labor market controls, whites earned 26% more than pardos with interviewer classification but only 17% more with self-classification, while the pardo-preto gap hardly changed (13%). Silva reported that interviewers tend to classify as pretos workers with lower socio-economic status. It could then be that workers who self-identify as pardos may be perceived by others as pretos (whites) when located at the bottom (top) of the conditional wage distribution, and

levels suggesting potential greater pay discrimination of pretos at the higher paying jobs. Thus, labor market discrimination seems more likely to occur when access of non-white workers to the higher-paying jobs within occupations cannot be denied on the basis of their observed productive attributes (Darity and Mason (1998)).

However, we cannot fully ascertain whether discrimination or other unobserved productivity differences causes the remaining return gaps. One intervening factor that could potentially explain the gaps is racial differences in education quality that are not well captured by our parental education variables. In the next section we attempt to infer the extent to which the return gaps can be explained by differences in education quality alone.

4.4 Quality of education

Table 6 presents the results of the effects of our proxies of education quality on the state-level average rates of return to education. As detailed in section 2.3, these come from second step (weighted) regressions of the first-stage-estimated returns (in percentage terms) for each cohort and state of birth for whites and non-whites separately on a dummy for non-whites, the pupil/teacher ratio and cohort fixed effects.[35] The race dummy captures the gap in average returns for non-whites purged of the effect of other control variables, including state-level education quality. The cohort dummies control for trends in the returns to education across cohorts. These are important since as illustrated in Figure 2 pupil-teacher ratios have declined systematically over time. Since the returns to schooling are lower for younger workers (in the early stage of a career) this could generate a spurious wrong-signed correlation between quality and the returns. We conduct the second-step analysis using the estimated returns from first stage regressions fitted to the full sample of workers and for the sub-sample of household heads with and without controls for father's education. This allows to document the effect of quality on all workers, and to see whether this effect is robust to sample definitions and controls for parental education.

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thus the similarity between pardos and pretos (whites) at the bottom (top) of the pay scale for each measured skill level.

[35] Of the 270 potential second stage observations (5 cohorts x 27 states x 2 race groups), we lose 4 observations because Brasilia became a separate state in 1960 and six additional observations because there were none or too few workers in the corresponding cohort-state-race cell. For the sample of household heads in the first stage regression we loose two additional state return observations for this latter reason.

Taken together these variables explain between one-third and close to one-half of the (weighted) variance in state-level education returns in Brazil (see the regression R^2s). We find that average returns to education are lower for workers educated in states with higher pupil-teacher ratios or lower education quality (columns C). A decrease in the pupil-teacher ratio by 10 students is associated with an increase in the average return to education by 0.9 percentage point. As a robustness check for the potential bias in this estimate due to selective migration, we ran the first stage regression without controls for state of birth effects so that the returns are not estimated from migrants (Reed and Lam (1999)). This had little influence in the estimate of the quality coefficient in the second stage.

Our estimated quality effect is remarkably similar to that of Card and Krueger (1992) for U.S. schools and male cohorts born between 1920 and 1950 and half as large as the effect documented by Case and Yogo (1999) for South African men using a similar approach.[36] The cohort dummies are highly significant and their omission (columns B) leads to a bias in the estimated quality coefficient as suggested above. The gap in average returns between whites and non-whites (pretos and pardos pooled together) measured at the state level is roughly 2 percentage points for the full sample of workers and almost 1 percentage point among household heads. Consistent with the previous results, the gap is reduced when we control for family background factors, proxied by father's education, in the first stage regression.

Note that the racial gap in returns remains essentially unaffected when we control for the education quality indicator. This is not entirely surprising since as a consequence of the aggregation there are no large differences in average pupil-teacher ratios at the state level between whites and non-whites. As noted in section 3, we tend to *overstate* the quality of education received by non-whites, particularly in states like the Southeast with average pupil/teacher ratios close to the national average and where the fraction of workers educated is similar across race groups. However, as pointed out by Card and Krueger (1992), since workers are assigned the average levels of school quality for their state of birth and cohort, aggregation does not induce classical measurement error biases in the quality estimates.

We can draw some inferences on the extent to which the residual racial gaps in returns could arise entirely from differences in education quality. Specifically, if the difference in pupil-teacher ratios between the schools attended by non-whites and whites is actually of 10 pupils, on average, then our analysis suggests that the observed racial gap in returns to education is due essentially to non-white's lower productive attributes including education quality, family background and community factors. However, we doubt that in general racial differences in education quality are so large. An informative benchmark is the quality gap between the Northeast and the South, the regions with the larger difference in pupil-teacher ratios in our data and the most acute racial divide in school attendance (see Table 2). From Figure 2 we see that the gap in pupil-teacher ratios between these two regions averaged 6 pupils per teacher, never exceeding 7 for any of the cohorts in our sample. Taking this average gap in pupil-teacher ratios, we conclude that differences in education quality could more plausibly account for about half of the observed gaps in average returns to education between whites and non-whites. Assuming that quality affects the returns similarly at all points of the conditional wage distribution, we are left with an average gap in returns of about 0.6 percentage points for non-whites with perhaps somewhat higher gaps for pretos in jobs with relatively higher pay. This returns gap implies average earnings about 7% lower for a non-white worker with a secondary education, and a 9% earnings disadvantage for those with a university degree.

5. Conclusions

In this study we examined the sources of racial earnings inequality in Brazil, in particular the role played by race, family background, the quantity and measured quality of education and heterogeneity in the earnings returns to these characteristics. The two main questions we address are how much of racial earnings inequality can be attributed to racial differences in measured productive characteristics of workers and whether conventional average earnings gaps can describe well the pay disadvantage of non-white workers at all points of the earnings scale.

With regards to the first question, we find that the bulk of racial earnings inequality is due to the advantage of whites in the accumulation of human capital (both own and parental education) and in the returns to their educational investments. The higher education returns for whites, in turn, are due partially to their more favorable socio-economic background and the fact that they

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[36] Card and Krueger (1992) report an estimated coefficient on the pupil/teacher ratio of -0.95 (percentage return) for a second stage regression that controls for state fixed effects. Case and Yogo (1999) report estimates between -1.8 and –2.0 for South African men age 24-34.

tend to attend school in states with relatively better quality. Although there remain important differences in labor market performance associated to skin color, unexplained racial gaps in absolute and relative earnings (education returns) are of second order.

Parental education not only increases children's educational attainment but it also grants substantial wage returns to them in their adult life. The racial pattern of wages gains from parental education could reflect returns to signals of unobserved family specific human capital for non-whites (specially for pretos) and returns to unmeasured components of school quality and/or family labor market connections for whites. The apparent convexification of the returns to parental education implies that the direct contribution of education to earnings inequality in Brazil is amplified by the inter-generational transmission of education inequality and this has an important interplay with race.

With respect to the second question, our findings are consistent with recent empirical studies that highlight an important role for unobserved worker heterogeneity in labor market performance. In particular, the mean return to education is not representative of the effect of education on wages for all workers. The returns are higher for workers at the upper conditional quantiles of the wage distribution. This suggests that education complements unobserved abilities in the generation of earnings which results in greater earnings inequality among workers at higher education levels.

Moreover, the gradient of skin color, in itself, seems to play a role in granting access to the better paying jobs. The evidence is consistent with potential greater pay discrimination at high salary levels conditional on observed characteristics. Market discrimination appears more likely to occur when the access of non-white workers to the relatively better paying jobs cannot be denied on the basis of their observed productive attributes. Moreover, pretos and pardos face a distinct disadvantage in education returns vis-à-vis whites depending on their position in the conditional wage distribution. While the labor market rewards the educational investments of pardos similar to those of white workers located at the top of the adjusted wage scale, pardos at the bottom are rewarded similar to pretos. This suggests that the common belief in Brazil that a better position in the socio-economic scale grants a fairer treatment in the labor market ("money whitens") may hold true only for pardos. This is consistent with the classic hypothesis in the race relations literature in Brazil that interracial marriage softens racial tensions by improving mobility opportunities for non-whites.

Although of second order, our estimated “unexplained” gaps in the level of earnings and in returns to education alone imply earnings about 16% lower, on average, than granted by measured productivity differences for a typical non-white worker with a secondary education, and close to an 18% earnings disadvantage for non-whites with a university degree.

Therefore, the agenda to reduce racial income inequality in Brazil requires a combination of actions to address the multiple dimensions of the problem. Actions to equalize opportunities in the access to education of adequate quality and to break the inter-generational trap of low education that hinders the socio-economic mobility of non-whites are central. These should promote higher schooling investments of non-whites facing high schooling costs by, for example, incentives (cash and in kind) to remain longer in school at least until completion of basic schooling (such as the Bolsa Escola program) and to enhance their learning levels. Educational programs for younger adults could have a double dividend by increasing the educational attainment of children and also their future wages if they can ensure completion of at least elementary schooling. Leveling the returns to educational investments is also key both to reduce the earnings disadvantage of non-whites and to encourage them to invest more in education. This requires increasing the quality of education received by non-whites by, for example, encouraging qualified teachers to work in disadvantaged schools, upgrading textbooks and curriculum, and adapting innovations to improve learning environments in disadvantaged schools and communities. There is also a need for enacting and enforcing anti-discrimination laws and establishing labor market intermediation services that facilitate well-educated non-whites greater access to better-quality jobs.

Finally, more research and policy analysis is needed on the causes and consequences of social exclusion and discrimination of non-whites and effective means to eliminate it, as well as greater efforts to raise awareness among government officials and social actors in Brazil on how these problems compromise the country’s prospects for development with social equity.

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