Why is poverty so high among Afro-Brazilians?
A decomposition analysis of the racial poverty gap

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Abstract

This study aimed to identify the major factors underlying the discrepancy in poverty levels between whites and blacks in Brazil. I performed an Oaxaca-Blinder-type decomposition in order to quantify the extent to which differences in observed characteristics (characteristics effect) account for this gap. The remaining unexplained part (coefficients effect) provides evidence on how these characteristics are differentially associated with the risk of poverty in each group. Our results show that the characteristics effect explains a large part of the discrepancy in poverty levels: education and labour variables explain one-half of the gap, and geographic and sociodemographic variables another two-fifths.

JEL Classification: D31, D63, J15, J82, O15.

Keywords: poverty, gap, race, skin colour, decomposition, Oaxaca-Blinder, Brazil, PNAD, labour market, participation, education, household characteristics

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Introduction

Brazil is well-known for its high inequality and poverty levels, even by Latin American standards. For instance, according to Londoño and Székely (2000), Brazil has the highest Gini index in Latin America and also the third-highest proportion of people below the US $2-a-day poverty line, after Honduras and Panama. One of the most striking features of income inequality in Brazil is the large socioeconomic discrepancy between population groups based on skin colour.

As a result of three and a half centuries of a slavery-based economy, Brazil has the second largest population of people of African descent after Nigeria. They account for almost one-half of all Brazilians: there were 11.6 million *pretos* (blacks) and 79.6 million *pardos* (persons of mixed race) in a total population of 184.4 million in 2005. Despite the absence of legally-sanctioned racism since slavery was abolished in 1888, this system has left a legacy of social discrimination against Afro-Brazilians, who are more likely to be members of socially disadvantaged groups. Indeed, the 2005 UNDP report specified the indicator for human development for Brazil in 2000 separately for each race. Whites alone (0.814) were placed among those countries with the highest human development level, ranking 44th (between Costa Rica and Kuwait), while Afro-Brazilians (0.703) fell in an intermediate group, ranking 105th (between El Salvador and Moldova). According to the main Brazilian household survey, the Pesquisa Nacional por Amostra de Domicílios, the mean per-capita income of Afro-Brazilians was only half that of whites. Furthermore, in 2005 about 33 percent of Afro-Brazilians lived in poor households whose incomes were below 50 percent of the median income of the country, in contrast to 14 percent of whites

falling into this group. This paper addresses this race-based discrepancy in poverty risk faced by Brazilians.

There are several possible explanations for poverty rates differing between racial groups. People of colour are clearly overrepresented in those groups that are at a higher risk of being below the poverty line. Indeed, compared with whites, a higher proportion of people of colour live in the poor north of the country, in the most-rural areas, and in families with a large number of children. While participation rates in the labour market do not differ substantially between these groups, blacks drop out of the educational system earlier and more often work in low-paying occupations. However, the extent to which each of these factors contributes to the overall discrepancy in poverty levels is unclear. Furthermore, there is evidence that the impact of individual characteristics on the poverty risk differs between racial groups. For instance, it is widely held that there is discrimination in the labour market against Afro-Brazilians, and there is also evidence that the quality of education varies between racial groups. Both of these factors result in Afro-Brazilians receiving lower returns from their schooling and from their experiences in the labour market, which reduces their ability to obtain the income necessary to escape from poverty.

The aim of this study was to identify the major factors responsible for the discrepancy in poverty levels between Brazilian racial groups. I used an Oaxaca-Blinder-type decomposition for logit regressions to measure the extent to which differences in observed geographic, sociodemographic, and labour characteristics, such as the number of children or years of schooling, account for this discrepancy (*characteristics effect*). The remaining unexplained part (*coefficients effect*) provides evidence on how the same characteristics are differentially associated with the poverty risk of each group. A detailed decomposition of both effects allows the

individual contribution of each characteristic to be determined. The results of this analysis will help in determining which social policies are more likely to be effective in reducing this race-based poverty gap.

The structure of the paper is as follows. In the following section I describe the data and review the main socioeconomic patterns between racial groups in Brazil. I then introduce the decomposition technique and present the empirical results. The final section summarises the main conclusions.

Poverty by race in Brazil

Data and definitions

Our data come from the 1992 and 2005 releases of the Brazilian National Household Survey (Pesquisa Nacional por Amostra de Domicílios, PNAD). This survey has been produced annually by the Instituto Brasileiro de Geografia e Estatística during the last quarter of each intercensus year since 1971, while between 1967 and 1970 it was produced quarterly. This database gathers information on the main demographic, socioeconomic, and labour characteristics at the household and individual levels for a nationally representative sample of the Brazilian population.[1] Since 1987 the survey has asked respondents to self-categorise their skin colour or race into one of five groups: *indígena* (indigenous), *branca* (white), *preta* (black), *amarela* (Asian), and *parda* (brown or mixed race).

Incomes are defined in this paper as monthly household cash incomes measured in per-capita terms and quantified in 2005 Brazilians reals (R$). There were 389,388 individuals in 2005 reporting their income: 180,480 whites; 180,456 browns; 26,129 blacks; and 2,323 either belonging to other minority groups (Asian and indigenous) or not classified. Sample weights must be applied to the observations in order to obtain unbiased estimates of the population parameters. In our analyses I

pooled browns and blacks into the same group (Afro-Brazilians or coloured people), since people of African descent might choose either of these categories due to the social stigma attached to blackness,[2] and because despite apparent differences in their socioeconomic performance, as is shown below, the probability of being at risk of poverty is the same in both groups after controlling for the relevant characteristics.

There is no official poverty line that applies to Brazil, so I defined the poverty line as 50 percent of the median per-capita income. In 2005 this poverty threshold corresponded to R$ 120 (about US$ 54), which also corresponds to the maximum to be eligible for the means-tested Bolsa Familia assistance program. This will enable our results to be used in the context of traditional administrative poverty lines in Brazil.[3] For the sake of robustness I also repeated the analysis based on an alternative threshold (60% of the median) and a standard equivalent scale (square root of the household size)[4].

I analyzed time trends in the racial poverty gap by comparing results from the 2005 and 1992 surveys. I chose 1992 rather than 1987 (the first year when race was reported) for two reasons: (1) for comparability, given that in 1992 some new definitions for labour variables were introduced by the PNAD, making the comparison with previous surveys difficult;[5] and (2) the 1980s in Brazil were characterised by high macroeconomic instability, with a high volatility also evident in the poverty indices. After stabilization was achieved at the beginning of the 1990s, poverty levels began a steady downward trend which has continued to the present day (Ferreira et al., 2006). In order to measure the changes in *absolute* poverty levels between 1992 and 2005, our poverty thresholds were kept fixed in real terms for both years at 2005 R$ 120, while for capturing changes in *relative* poverty the threshold

for each year corresponds to 50 percent of the contemporary median income; that is, 2005 R$ 85.24 in 1992 and 2005 R$ 120 in 2005.[6]

Poverty and households characteristics in Brazil

In 2005 the average per-capita income in Brazil was R$ 441, and about 23 percent of the population is considered to have been poor according to the poverty line described above. The magnitudes of racial differences in Brazil are striking and highly statistically significant. Table 1 indicates that the 2005 poverty rate is 14 percent among whites but 33 percent among Afro-Brazilians (26% for blacks and 34% for browns). Further, the average monthly per-capita income for whites in 2005 (R$ 592) was twice that of Afro-Brazilians (R$ 310 for blacks and R$ 275 for browns). Note that the Asian minority (mainly of Japanese descent) exhibits an average per-capita income that is 87 percent higher than that of whites and a poverty rate of only 7 percent, while the indigenous minority shows similar patterns to those of blacks and browns. However, these minorities were excluded from the subsequent analyses since they account for less than 1 percent of the population.

Table 1

Figure 1 presents the skin-colour distributions across income deciles. Clearly, the share of Afro-Brazilians decreases with per-capita income: black people account for 71 and 19 percent of the population in the bottom and top deciles, respectively, in contrast to the corresponding values for whites of 28 and 79 percent.

Figure 1

The poverty rates differ between Afro-Brazilians and whites for all household types considered in table 2, but not to the same extent. The ratio of poverty rates for people of colour to those for whites is higher for households living in urban areas in the rich south and southeast of the country. This ratio increases with the number of

years of schooling completed by the household head, and is larger when he or she is economically inactive or works in the formal sector in industries other than agriculture and domestic service.

Table 2

This large race-based discrepancy in poverty rates may result primarily from Afro-Brazilians being overrepresented in those socioeconomic groups at a higher risk of poverty. This can be inferred from the data on most of the groups reported in table 2 as exhibiting a ratio of poverty levels lower than that for the whole population, which is evidence of a composition effect. Indeed, as table 3 indicates, people of colour account for at least 70 percent of the population in states located in the two poorest geographic regions in Brazil (the north and northeast). In contrast, whites represent 81 and 58.5 percent, respectively, of the population in two of the richest regions in the south and southeast of the country, with the latter including the main metropolises of São Paulo and Rio de Janeiro. Afro-Brazilians represent the majority (55.5%) in only one relatively rich region, the centre-west, where the capital (Brasilia) is located. Differences in population shares are even more pronounced when rural and urban areas are distinguished, given that 20 percent of browns live in the former, compared with only 13 percent of whites (and 12% of blacks). As a consequence, whites are underrepresented in the rural areas of all regions (where poverty is twice as high as in urban areas) except for the southern states.

Table 3

People of colour tend to live in larger households: they have 4.6 members on average compared with 4.0 for whites (table 4). Afro-Brazilian households have more dependents, especially children (on average 1.6 are aged 15 years or less compared with 1.2 for whites), but also adults (0.7 are between 16 and 45 years), compared with

0.6 for whites. However, the number of older dependents (older than 45 years) in the household is slightly lower for Afro-Brazilians (0.13) than for whites (0.15). This of course reflects Afro-Brazilians being, on average, younger than whites. This is compensated by the number of people receiving incomes in the household also being larger for Afro-Brazilians, although the difference relative to whites is less, reflecting a higher degree of dependency in coloured households: on average 48 percent of their household members do not receive incomes, in contrast to 42 percent in white households.

Table 4

One of the main characteristics that could explain the racial poverty gap is education. It is well-documented that Brazil exhibits one of the most unequal distributions of years of education in the world (De Ferranti *et al*., 2003). Although great progress has been made in this indicator during recent decades, the Gini index for years of schooling among those aged between 25 and 65 years was still 41 percent in 2001, which is the highest level in Latin America after Bolivia (43.4) and a few Central American countries, and greatly different from the other main economies in the region (36.6 in Mexico and 22.2 in Argentina). This fact is reflected in the racial distribution, given that people of colour drop out of the educational system at a younger age. Table 4 indicates that the adult illiteracy rate is 15 percent among Afro-Brazilians, in contrast to 7 percent for the white population. Additionally, the proportion of people of colour aged at least 25 years who had no education is about 21 percent and the proportion with 15 or more years of studies is lower than 4 percent, while the corresponding percentages are 10 and 12 percent for whites. Differences in the quality of education have often been stressed as important reasons for inequality of opportunity in Brazil (Leite, 2005), because students from the poorest families are

overrepresented in public schools, which typically provide education of lower quality. Indeed, according to our own estimates, the proportion of students aged 16 years or less attending a private school is 22 percent for whites but only 11 percent for Afro-Brazilians. This difference in proportions increases for those aged over 18 years: 48 percent of whites and 21 percent of Afro-Brazilians attend a private institution. There is also evidence that Afro-Brazilians attending university are underrepresented in those degrees that lead to higher earnings (UNDP, 2005).

Finally, table 5 reports how different racial groups perform in the labour market. The proportion of people aged at least 16 years who are employed is similar in both groups, about 64 percent, and members of both groups also work a similar number of hours per week (43 hours). There is only a smaller participation (of 1%) in the case of coloured females, who also work 1 hour less than whites. Afro-Brazilian males and females show higher activity rates, but these are offset by a greater risk of unemployment. There is strong evidence of racial segregation by occupation and industry, with whites being overrepresented among employers, managers, and professional employees in both the public sector and the formal private sector; and being underrepresented among employees and the self-employed in agriculture and domestic services, as well as among informal and unpaid workers. Nevertheless, the main racial difference is evident in average hourly earnings, which is R$ 6.50 for white men but only R$ 3.60 for coloured workers (note that the difference is only slightly smaller for females). As a consequence, average monthly earnings are R$ 1,034 for whites but only R$ 550 for Afro-Brazilians. The extent to which these differences in earnings between white and coloured workers in Brazil reflect pay discrimination and segregation has been widely explored in recent years. For instance, Arcand and D'Hombres (2004) concluded that wage discrimination accounted for 36

and 23 percent of the racial wage discrepancy for blacks and browns, respectively, while occupational segregation explained an additional 8 and 5 percent. Campante *et al.* (2004) reported 26 percent of wage discrimination among Afro-Brazilians, while Leite (2005) found a reduced value of 11 percent after controlling for differences in the mother's education, emphasizing the role played by intergenerational transmission of education in the observed race-based pay gap.

Table 5

Methodology: multivariate decomposition analysis with nonlinear regression

I examined the contribution of household characteristics to the differential in poverty rates among racial groups in Brazil by applying an extension of the well-known regression-based Oaxaca-Blinder decomposition approach to the probability of being poor, estimated using logit regressions.[7] In our framework, the *i*-th person in group *g* is considered poor when his or her household income, y_i^g, falls below the poverty line, *z*. Then, the likelihood of this person being poor (P_i^g) is given by

$$P_i^g = \Pr\left(y_i^g < z\right) = F(X_i^g \hat{\beta}^g) = \frac{\exp\left(X_i^g \hat{\beta}^g\right)}{1+\exp\left(X_i^g \hat{\beta}^g\right)}, \qquad \textbf{(1)}$$

where *F* represents the logistic probabilistic cumulative distribution, X_i^g is a vector of characteristics describing household *i*, and $\hat{\beta}^g$ is the associated vector of coefficient estimates. I estimated regressions separately for whites and Afro-Brazilians.

Given that poverty is the consequence of lacking enough household income to make ends meet, I included among the explanatory variables a number of characteristics of the household reference person that may have influenced his or her ability to earn income. These included demographic variables such as gender**,** age, attained education (years of schooling and illiteracy status), geographic mobility (indicating the area of origin); as well as a set of variables describing the labour force

participation of the head and the characteristics of the job. These variables included several types of occupation according to the activity (agriculture, domestic service, or other industries), sector (formal or informal), required skills (managerial/professional occupation or not), employment status (self-employed or employee), and the number of average weekly hours worked. I also included the type of family, as this may also affect the ability of the family head to get a job: I distinguished among families composed of one single person, a married couple, single mothers, and others, as well as a dummy indicating whether there is more than one family in the household. Given that family income can also be provided by other family members and that the presence of dependents may increase family needs but not income, I included the number of other family members as well, distinguishing the number of dependents (of different ages) from the number of labour and non-labour income receivers (by years of schooling and gender, and in the case of those who were employed, also by age and characteristics of the job). Other variables included were the state of residence and whether the area is rural or urban, in order to take into account potential differences in economic opportunities. Since I estimated the probability of a person being poor with all explanatory variables collected at the household level, the standard i.i.d. assumption is violated. For this reason, our estimated robust standard errors took into account individuals being "clustered" across households.[8]

This simple econometric specification allows us to identify the statistical association between the probability of being poor and each family attribute when the other characteristics are controlled for. But I should be cautious in the interpretation of the results as no control for possible endogeneity sources was made, and no causality relationship can be assessed.[9] Thus, these regressions have to be understood in the context of poverty decompositions by subpopulations in which, unlike standard

poverty decomposition techniques, I identify the statistical association between each characteristic and the probability of being poor while controlling for the rest of attributes.

One appealing property of this logit framework is that the head-count ratio of poverty in group *g*, H^g, is equal to the average predicted probability for this group (with population N^g):

$$H^g = \overline{P^g} = \overline{F(X_i^g \hat{\beta}^g)} = \frac{1}{N^g}\sum_{i=1}^{N^g} F(X_i^g \hat{\beta}^g). \qquad \textbf{(2)}$$

This property allows us to use the average estimated probabilities to break the observed differential in poverty rates among two given groups, 0 (whites) and 1 (blacks),[10]

$$H^1 - H^0 = \overline{P^1} - \overline{P^0} = \overline{F(X^1\beta^1)} - \overline{F(X^0\beta^0)}, \qquad \textbf{(3)}$$

into two distinct terms, when 0 is taken as the reference group:

$$H^1 - H^0 = \left[\overline{F(X^1\beta^1)} - \overline{F(X^0\beta^1)}\right] + \left[\overline{F(X^0\beta^1)} - \overline{F(X^0\beta^0)}\right], \qquad \textbf{(4)}$$

These two terms represent, respectively, the *aggregate characteristics effect* (first term on the left-hand side of equation) and the *aggregate coefficients effect* (second term). There is wide consensus on this type of decomposition in the case of non-linear probability regressions.[11]

To evaluate the individual contribution of each variable (or set of variables) to the total difference, which is usually referred to as the *detailed decomposition*, I follow the method proposed by Yun (2004), which is valid for any nonlinear function *F* and is a generalization of the decomposition of Even and Macpherson (1990, 1993) of only the characteristics effect.[12] The detailed decomposition is then given by

$$H^1 - H^0 = \sum_{k=1}^{K} W_{\Delta X}^k \left[\overline{F(X^1\beta^1)} - \overline{F(X^0\beta^1)} \right] + \sum_{k=1}^{K} W_{\Delta\beta}^k \left[\overline{F(X^0\beta^1)} - \overline{F(X^0\beta^0)} \right], \quad \textbf{(5)}$$

where $W_{\Delta X}^k$ and $W_{\Delta\beta}^k$ are, respectively, the individual relative contributions of characteristic k (k=1, …, K) to the overall characteristics and coefficients effects such that

$$W_{\Delta X}^k = \frac{\left(\bar{X}_k^1 - \bar{X}_k^0\right)\beta_k^1}{\left(\bar{X}^1 - \bar{X}^0\right)\beta^1}, \quad \sum_{k=1}^{K} W_{\Delta X}^k = 1; \quad W_{\Delta\beta}^k = \frac{\bar{X}_k^0\left(\beta_k^1 - \beta_k^0\right)}{\bar{X}^0\left(\beta^1 - \beta^0\right)}, \quad \sum_{k=1}^{K} W_{\Delta\beta}^k = 1. \quad \textbf{(6)}$$

These weights were obtained in Yun (2004) in two stages: (1) the value of the average of F, $\overline{F(X^g\beta^g)}$ was approximated by using that of the function evaluated at the sample average of the exogenous variables, $F(\overline{X^g\beta^g})$; and (2) then a first-order Taylor-series expansion was used to linearize the characteristics and the effects of the coefficients around the sample mean.[13]

This technique has a few advantages over other proposed methods that appear in the literature. First, the weights are quite transparent and simple to compute because this only requires estimates of the coefficients and sample means of the characteristics. Secondly, this procedure overrides the problem of path dependency that is common to all sequential approaches to nonlinear models, where values of characteristics and/or coefficients of one group need to be switched with those of the other group.[14] Thirdly, unlike these sequential approaches, the detailed characteristics effect can be obtained without making any assumptions to match individuals of one group with the characteristics of another.[15] Finally, the original Oaxaca-Blinder approach is shown to be a particular case of this decomposition when F is a linear function.

However, an additional and well-known problem that needs to be addressed is that detailed decomposition of the coefficients effect suffers from severe identification difficulties.[16] This is because the contribution of a dummy variable to this effect will vary with the choice of the reference group, and this applies to any set of dummy variables.[17] For this reason, several researchers have undertaken detailed decompositions of only the characteristics effect, which is not affected by this problem.[18] To tackle this difficulty I use normalised regressions in computing weights in **(5)**, as proposed by Suits (1984), Gardeazabal and Ugidos (2005) and Yun (2005a, b). This method has the advantage of being invariant to the "left-out" reference category in computing the contribution of dummy variables to the detailed coefficients effect. Further, it alters neither the detailed characteristics effect nor the contribution of continuous variables to the coefficients effect.

After suppressing group superscripts for simplicity, I can rewrite our model in **(1)** as

$$P_i = F\left(\alpha + \sum_{l=1}^{L} X_l \hat{\delta}_l + \sum_{m=1}^{M} \sum_{k_m=2}^{K_m} D_{mk_m} \hat{\beta}_{mk_m}\right), \qquad \textbf{(7)}$$

where there are L continuous variables X, and M sets of categorical variables D, and where the m-th set has K_m categories and K_m–1 dummy variables in the equation, with the reference group being the first category of each set of dummy variables. Then, the normalised equation is given by

$$P_i^* = F\left(\alpha^* + \sum_{l=1}^{L} X_l \hat{\delta}_i^* + \sum_{m=1}^{M} \sum_{k_m=1}^{K_m} D_{mk_m} \hat{\beta}_{mk_m}^*\right), \qquad \textbf{(8)}$$

where the parameters for the intercept, continuous variables, and dummy variables are, respectively,

$$\hat{\alpha}^* = \hat{\alpha} + \sum_{m=1}^{M} \overline{\hat{\beta}}_m;$$
$$\hat{\delta}_i^* = \hat{\delta}_l, i = 1,...,L; \quad \textbf{(9)}$$
$$\hat{\beta}_{mk_m}^* = \hat{\beta}_{mk_m} - \overline{\hat{\beta}}_m, k_m = 1,...,K_m, m = 1,...,M.$$

For the omitted categories in the original regression, $\hat{\beta}_{m1} = 0, \ \forall m = 1,...,M$. In this way I can compute the decomposition to identify characteristics and coefficients effects for each category, including the reference group in the original equation.[19]

Finally, in order to provide information about the statistical significance of the characteristics and coefficients effects, standard errors will be provided following the Delta method sketched in Yun (2005b).

Results

Poverty regressions

Our analysis started with multivariate logit regressions explaining the likelihood of a person being poor, conditioned on their household characteristics. The benchmark person is a lone male aged between 16 and 24 years, illiterate, with no schooling, employed in the informal agrarian sector in a rural area in Minas Gerais (southeastern region), and born in the same municipality as where he currently lives.

First, a regression for the pooled sample of Brazilians run with dummy variables for all non-white groups showed that being black, brown, or indigenous was strongly positively correlated with the likelihood of being poor (with coefficients of around 0.30 and higher), while being Asian showed no significant effect.[20] The results are presented in the Appendix. However, there was no significant difference between blacks and browns after controlling for other characteristics.

I then estimated regressions separately for whites and Afro-Brazilians; the results are also presented in the Appendix.[21] In general, our results in 2005 suggest that the coefficients are similar in sign for both racial groups, although they differ in

magnitude and statistical significance. Compared with the reference case, living in an urban area and in the centre-west and south of the country, as well as in states such as Rio de Janeiro, São Paulo, or Santa Catarina has a significant and negative effect on poverty risk, which is generally larger for Afro-Brazilians, while living in north-eastern and some northern states has a significant and strongly positive effect (more clearly in the case of whites). Single-mother-headed households are more likely to be poor in both groups, as are Afro-Brazilian households headed by other females. Single-family households and those comprising a couple with many dependents face a higher risk of being poor. Indeed, the number of dependents is significantly and largely related to poverty, especially in terms of the number of young children and of adults older than 45 years. The older and more educated the household head, the lower the probability of being poor. The risk of falling into poverty decreases when the head is originally from a different municipality, especially when this is in the centre-western region or abroad.

The risk of poverty increases when the head of the household is unemployed and decreases when he or she is economically inactive or, especially, when he or she works as an employer or as a skilled formal employee in industries other than agriculture or domestic service. Working more hours has a greater effect on reducing the poverty risk for whites. The poverty risk increases with the number of employed children (aged between 10 and 15 years) in coloured households, which reflects the fact that their contribution to household income is too small to compensate for the increase in household needs. However, the presence of more employed adults is generally associated with lower poverty. This latter effect increases with an increased number of years of education, increased weekly hours of working, and a decreased number of female workers. The effect is also substantially larger for workers in

formal and skilled occupations. The number of unemployed adults in the household receiving non-labour income, especially if they are male and with either low or high education, is also significantly negatively correlated with the likelihood of the household members being poor. These effects appear to be stronger for whites and have a U-shaped relationship with education. This might be due to those with low education being more likely to be eligible for social assistance programs, while those with higher education have better access to other sources of income (e.g., pension benefits or properties).

Decomposition analysis: aggregate and detailed effects

Based on the above estimates, the poverty gap between Brazilian racial groups, shown in table 6, was decomposed into aggregate characteristics and coefficients effects as indicated in table 7. The aggregate decomposition shows that combining the observed characteristics explained a large proportion of the raw difference in poverty levels between Afro-Brazilians and whites (87.9% according to the estimated model). This means that if blacks had the same characteristics as whites in Brazil, the observed discrepancy in poverty rates (18.4%) would be narrowed to 2.2 percent – this is the *conditional racial poverty gap*. This value corresponds to the remaining unexplained part (that is, the coefficients effect) accounting for 12.1 percent of the raw difference.

Tables 6 and 7

A detailed decomposition of the characteristics effect, also displayed in table 7, shows that three main factors account for the entire explained discrepancy: (1) education and labour activity of household members account for 46.7 percent of the raw gap, (2) demographic factors account for 24 percent, and (3) geographic factors account for 17.3 percent.[22] The level of the first factor mainly results from the

lower education of black household heads (20.1%) and their overrepresentation in low-paid occupations (10.9%), although the education of other working household members and their performance in the labour market are also important (15.6%). The other two major factors are blacks having more dependent children and young adults (both summing to 22.4%), and residing in the poorest states of the country (17.1%). The number and education of non-labour income receivers, the area of residence (urban or rural), and other demographic characteristics (that is, sex, age, type of family, and mobility status) appear to play only marginal roles after controlling for the other factors. It should be noted that no characteristic is negatively related to the discrepancy in poverty rates; only the lower number of dependent adults older than 45 years in Afro-Brazilian households has a negative sign but its significance is low. Thus, there is virtually no *advantage* of being Afro-Brazilian when facing the risk of poverty.

I revealed that differences in characteristics explain the largest part of poverty discrepancies. However, there is also evidence that the same factors can have different degrees of association with the race-based variation in the probability of being poor. The overall coefficients effect is 12.1 percent of the raw discrepancy, as mentioned above, and is globally significant. Table 7 also provides the detailed decomposition of the coefficients effect using the normalised regressions. The most salient point is that after controlling for education and occupation, the number of hours worked by Afro-Brazilian household heads is negatively related to their poverty risk compared with whites, explaining a significant 5.2 percent of the raw poverty gap. The underlying reasons for these coefficients effects are unclear given that this is essentially the *unexplained* part of the model, but the existing empirical evidence suggests that they could result from differences in the quality of education combined with the

persistence of labour discrimination against Afro-Brazilians, all of which reduce their opportunities in the labour market. This could also explain why there are non-negligible coefficients effects for geographic-related variables such state, area of residence, family type, and even mobility status, indicating that Afro-Brazilians obtain less advantage from living in (or moving to) urban areas and rich states.

Finally, I addressed the issue of whether the major factors explaining the race-based poverty discrepancy have changed with time. This was achieved by comparing the results for 2005 with those for 1992, which are also given in Table 7 for the absolute (poverty line fixed in real terms) and relative case (poverty line expressed as a percentage of the contemporary median income). The absolute poverty rate in Brazil (using the fixed 2005 R$ 120 poverty line) has declined sharply, from 36 percent of the overall population in 1992 to 23 percent in 2005. This reduction has benefited both racial groups, and the raw racial poverty gap also decreased during this period from 25.9 to 18.4 percent.[23] However, the reduction in the *conditional* gap or coefficients effect was small and statistically insignificant at 95 percent of confidence, from 3.2 percent in 1992 to 2.2 percent in 2005. Thus, most of the decrease in the difference in poverty rates by race was due to the characteristics effect: in 1992 (a 23% gap) and 2005 (15.8% gap) this explained 87.5 and 87.9 percent, respectively, of the raw gap. This statistically significant decrease in the characteristics effect was entirely due to lower contributions from three factors: the number of dependent children, from 6.5 to 4.1 percentage points (that is, from 25.6 to 22.4% of the gap); state of residence, from 4.6 to 3.1; and education of the head, from 5.3 to 3.7; even if in these two last cases the relative contribution remained roughly constant. At the same time, the education and labour characteristics of non-head household members became a much more important factor for explaining the race-based poverty gap

during the same period (from 11.1 to 15%), because in this case the explained gap showed more persistence.

The progress in reducing poverty in Brazil has been rather modest based on a *relative* poverty concept (50% of the contemporary median): from 26.4 percent of the population being considered poor in 1992 to 23.5 percent in 2005.[24] The raw racial difference was reduced only from 21.0 to 18.4 percent. In fact, the *conditional* poverty gap slightly rose, from 1.6 to 2.2 percent, in that period, with this change having low statistical significance; while the gap explained by characteristics significantly fell, from 19.5 to 16.2 percent, due to all three factors combined (geographic, sociodemographic, and labour characteristics). Regardless of whether I use an absolute or a relative notion of poverty to compare the data from 1992 and 2005, it is clear that even if the characteristics effect still explains a large part of the raw racial poverty gap, this share is now smaller, indicating the increasing role played by persistent unobservable factors (coefficients effect).

Conclusions

In this study I investigated why poverty in Brazil is so much higher for Afro-Brazilians than for whites. I have shown that this discrepancy affects most types of household, but especially those with more educated members who live in urban areas in the rich southern and southeast states of the country. Our use of an Oaxaca-Blinder extension for nonlinear probability regressions revealed that differences in observed characteristics account for almost 88 percent of the difference in poverty levels between whites and Afro-Brazilians. Labour-related characteristics fuelled by differences in years of schooling of household members contribute the most, at least one-half of what can be explained. Geographic and demographic factors (the number of dependents) also explain another significant part of the raw gap.

I have additionally shown that despite this large characteristics effect**,** there remains a significant unexplained part reflected by the lower association between the number of hours worked and the risk of poverty (especially those worked by the household head). This is the consequence of the lower opportunities for Afro-Brazilians in the labour market, which probably results from unequal access to high-quality education and persisting segregation and discrimination in the labour market.

The sharp reduction in the skin-colour-related differences in the incidence of absolute poverty from 1992 to 2005 was driven by geographic and demographic variables, with the factors of education and performance in the labour market showing smaller changes and hence becoming more important explanatory factors. The decrease in the racial gap was due to a lower characteristics effect, but there was no significant reduction in the conditional gap (regardless of whether poverty is measured in absolute or relative terms).

The main policy implication of this decomposition analysis is that the most effective measures for removing race-based differences in poverty risk are bridging the huge educational gap between black and white Brazilians, and compensating poor households with dependent children, as well as reducing regional disequilibria, even if some of these changes would only be effective over a long period. The Bolsa Familia program, in which cash payments to poor families with children are conditional on their schooling, may represent a step in the right direction for reducing both the overall poverty and the race-based poverty gap.

Table 1. Poverty and skin colour/race in Brazil in 2005

Skin colour/race	Population (%)		Mean income (R$)		Poverty rate (%)	
	Estimate	Standard errors	Estimate	Standard errors	Estimate	Standard errors
White	50.49	0.09	591.5	2.5	14.45	0.09
Afro-Brazilian	48.83	0.09	279.2	1.0	32.84	0.11
Black	6.32	0.04	309.7	3.0	27.10	0.30
Brown	42.51	0.09	274.8	1.0	33.68	0.12
Asian	0.48	0.01	1,108.5	42.9	7.47	0.66
Indigenous	0.18	0.01	340.1	26.6	34.77	1.84
All	100		440.5	1.4	23.46	0.07

Note: Excluding rural areas of Rondônia, Acre, Amazonas, Roraima, Pará, and Amapá.

Source: Author's calculations using PNAD (2005) data.

Table 2. Poverty rates by characteristics and skin colour in Brazil in 2005
(percentage of the corresponding group below the poverty line)

	Whites	Afro-Brazilians	Ratio	
	(1)	(2)	Estimate (2)/(1)	Standard error*
All households	14.45	32.84	2.27	0.02
Residence				
North	21.31	30.54	1.43	0.03
Northeast	36.48	48.19	1.32	0.01
Southeast	8.83	20.39	2.31	0.04
South	10.44	21.93	2.10	0.05
Centre-west	12.85	21.51	1.67	0.04
Urban	33.51	55.83	1.67	0.02
Rural	11.66	27.53	2.36	0.02
Household-head years of schooling				
0	32.02	47.46	1.48	0.02
1–3	24.86	43.93	1.77	0.02
4–7	17.22	32.00	1.86	0.02
8–10	11.98	22.87	1.91	0.04
11+	3.28	9.46	2.88	0.08
Household-head employment status				
Inactive	11.42	25.76	2.26	0.04
Unemployed	50.09	66.41	1.33	0.02
Informal employee in agriculture	49.80	67.92	1.36	0.02
Informal employee in domestic service	31.78	43.69	1.37	0.04
Informal employee in other industries	16.65	35.32	2.12	0.05
Formal employee in agriculture	24.01	37.89	1.58	0.06
Formal employee in domestic service	14.97	25.47	1.70	0.12
Formal employee in other industries (manager or professional)	0.43	2.34	5.40	1.14
Formal employee in other industries (other occupations in private sector)	8.20	17.63	2.15	0.05
Formal employee in other industries (other occupations in public sector)	5.26	12.97	2.47	0.13
Self-employed in agriculture	37.24	62.28	1.67	0.02
Self-employed in other industries	13.09	29.75	2.27	0.04
Employer	1.98	9.99	5.04	0.39
Unpaid and others	27.39	47.22	1.72	0.05

Note: Excluding rural areas of Rondônia, Acre, Amazonas, Roraima, Pará, and Amapá.
* All racial poverty ratios are significantly larger than one (at 95% confidence level) with p-value equal to 0.

Source: Author's calculations using PNAD (2005) data.

Table 3. Household characteristics in Brazil in 2005: distribution of population by region of residence and skin colour

			Population distribution (%)				
	Average income (R$)	Poverty rate (%)	Whites	Afro-Brazilians	Others	Racial gap (1)-(2)	
Residence			(1)	(2)		Estimate	Standard Errors*
North	323.1	28.15	25.66	73.71	0.63	-48.05	0.44
Northeast	248.1	44.73	29.50	70.16	0.34	-40.66	0.27
Southeast	543.7	13.51	58.47	40.65	0.88	17.82	0.29
South	529.7	12.59	80.78	18.58	0.64	62.20	0.34
Centre-west	498.0	17.82	43.53	55.58	0.89	-12.04	0.48
Urban	4854	19.14	52.25	47.01	0.74	5.24	0.19
Rural	199.4	46.71	41.00	58.67	0.33	-17.67	0.43
All	**440.5**	**23.46**	**50.49**	**48.83**	**0.68**	**1.66**	**0.17**

Note: Excluding rural areas of Rondônia, Acre, Amazonas, Roraima, Pará, and Amapá.
* All proportions are significantly different across groups at 95% confidence level (with p-value equal to 0).

Pearson chi2 for equality between whites and Afro-Brazilians distributions rejects equality in both cases: 2.4e+07 (regions) and 1.3e+06 (urban/rural),

Source: Author's calculations using PNAD (2005) data.

Table 4. Household characteristics and skin colour in Brazil in 2005

Household members and income	Whites (1)	Afro-Brazilians (2)	Racial gap Estimate (1)-(2)	Standard Errors*	K-S test**
No. of household members	4.00	4.64	-0.64	0.007	0.129
No. of dependents***	1.89	2.46	-0.58	0.006	0.125
Aged <10 years	0.72	1.00	-0.29	0.004	0.089
Aged 10–15 years	0.44	0.59	-0.15	0.003	0.067
Aged 16–45 years	0.58	0.74	-0.16	0.003	0.072
Aged 46+ years	0.15	0.13	0.02	0.001	0.017
No. of workers receiving earnings	1.72	1.77	-0.05	0.004	0.016
No. of non-workers receiving non-labour income	0.40	0.41	-0.01	0.002	0.018
Household dependency ratio (%)	42.1	48.2	-6.07	0.091	0.099
Age					
Mean	31.82	28.77	3.05	0.071	0.065
Distribution (% in each interval)					
<16 years	26.20	30.22	-4.02	0.16	
16–24 years	16.17	18.21	-2.05	0.13	
25–55 years	42.83	40.51	2.32	0.17	
56+ years	14.80	11.06	3.75	0.12	
Education					
Illiteracy rate (% aged 15+ years)	6.96	15.30	-8.34	0.13	
Years of education (population aged 25+ years)					
Mean	7.47	5.45	2.02	0.02	0.149
Distribution (% in each interval)					
0	9.92	20.61	-10.69	0.17	
1–3	11.47	16.19	-4.71	0.16	
4–7	27.14	28.20	-1.06	0.21	
8–10	13.45	12.62	0.83	0.16	
11–14	26.10	19.01	7.09	0.20	
15+	11.92	3.38	8.54	0.13	

* Standard errors in measurement of the racial gap by characteristic.
All differences are significant at 95% level (with p-value equal to 0).

** Two-sample Kolmogorov-Smirnov tests for equality of distribution functions.
In all cases equality is rejected at 95% level (with p-value equal to 0).

*** Dependents: all children younger than 10 years and all individuals above that age not receiving any income.

Excluding rural areas of Rondônia, Acre, Amazonas, Roraima, Pará, and Amapá.

Source: Author's calculations using PNAD (2005) data.

Table 5. Labour market performance in Brazil by skin colour (people aged 16+ years) in 2005

	All			Males			Females		
Labour status (% population)	**W**	**A-B**	**s.e.**	**W**	**A-B**	**s.e.****	**W**	**A-B**	**s.e.**
Inactive	30.60	28.83	0.19	18.21	16.77	0.23	41.48	40.40	0.28
Unemployed	5.61	7.49	0.10	5.02	6.60	0.14	6.13	8.34	0.15
Employed	63.79	63.79	0.20+	76.77	76.64	0.25+	52.39	51.26	0.29
Informal employee in agriculture	1.37	3.51	0.06	2.62	6.46	0.12	0.27	0.68	0.04
Informal employee in domestic service	2.73	4.60	0.08	0.29	0.50	0.04	4.87	8.54	0.14
Informal employee in another industry	8.38	9.43	0.12	10.67	12.78	0.19	6.36	6.21	0.14
Formal employee in agriculture	0.94	1.47	0.05	1.77	2.70	0.09	0.21	0.30	0.03++
Formal employee in domestic service	1.15	1.55	0.05	0.27	0.30	0.03+	1.92	2.75	0.09
Formal employee in another industry (manager or professional in private sector)	2.84	0.88	0.06	3.22	1.03	0.09	2.49	0.74	0.07
Formal employee in another industry (manager or professional in public sector)	17.73	14.43	0.16	23.62	20.40	0.25	12.55	8.70	0.18
Formal employee in another industry (other occupations in private sector)	2.14	0.93	0.05	1.37	0.56	0.06	2.82	1.28	0.08
Formal employee in another industry (other occupations in public sector)	4.19	3.95	0.08	4.39	4.06	0.12	4.02	3.85	0.11+
Self-employed in agriculture	2.66	3.75	0.07	5.08	6.59	0.14	0.53	1.02	0.05
Self-employed in another industry	10.72	10.81	0.13+	14.03	13.95	0.21+	7.80	7.80	0.15+
Employer	3.84	1.56	0.07	5.94	2.43	0.12	2.00	0.72	0.07
Unpaid and others	5.12	6.82	0.10	3.51	4.88	0.12	6.53	8.67	0.15
Weekly hours*	42.90	42.44	0.08	45.83	45.29	0.09	38.81	37.87	0.12
Hourly earnings (R$)*	6.51	3.57	0.06	7.07	3.71	0.09	5.73	3.34	0.08
Monthly earnings (R$)*	1,033.9	550.2	7.6	1,191.4	616.9	11.2	813.53	442.88	8.9
Per capita income	591.5	279.3	2.70	597.4	283.4	4.03	586.2	275.2	3.63
Equivalent income ($\sqrt{household\ size}$)	1,062.1	534.4	4.36	1,077.4	540.8	6.46	1,048.0	528.2	5.89
Equivalent income (modified OECD)	1,179.6	567.3	5.13	1,195.2	575.2	7.60	1,165.4	559.5	6.93

* Average computed for workers receiving labour income.

** Standard error in measurement of the gap between groups. All are significant at 95% level except:
+ non significant at 90%
++ significant at 90% but not at 95%

Pearson chi2 for equality between distributions of whites and Afro-Brazilians by labour status rejects equality in all cases:

chi2 test	**all**	**males**	**females**
inactive, unemployed, employed	2.1e+05	8.5e+04	1.2e+05
inactive, unemployed, detailed occupation	3.4e+06	1.8e+06	1.7e+06
detailed occupation (only those employed)	3.1e+06	1.7e+06	1.5e+06

Note: Excluding rural areas of Rondônia, Acre, Amazonas, Roraima, Pará, and Amapá.

Source: Author's calculations using PNAD (2005) data.

Table 6. Poverty rates and the racial poverty gap in Brazil: 1992 and 2005

	2005 poverty line (50% median income =2005 R$120)	**1992** fixed/absolute poverty line (2005 R$120)	**1992** relative poverty line (50% median income)
Poverty rates			
All	23.46	36.40	26.32
Whites	14.45	24.75	16.84
Afro-Brazilians	32.84	50.62	37.86
Raw racial poverty gap	18.38	25.87	21.01
standard error	0.14	0.18	0.17

Note: Excluding rural areas of Rondônia, Acre, Amazonas, Roraima, Pará, and Amapá.

Source: Author's calculations using PNAD (1992 and 2005) data.

Table 7. Decomposition analysis of the racial poverty gap in Brazil from 1992 to 2005 (Afro-Brazilians and whites)

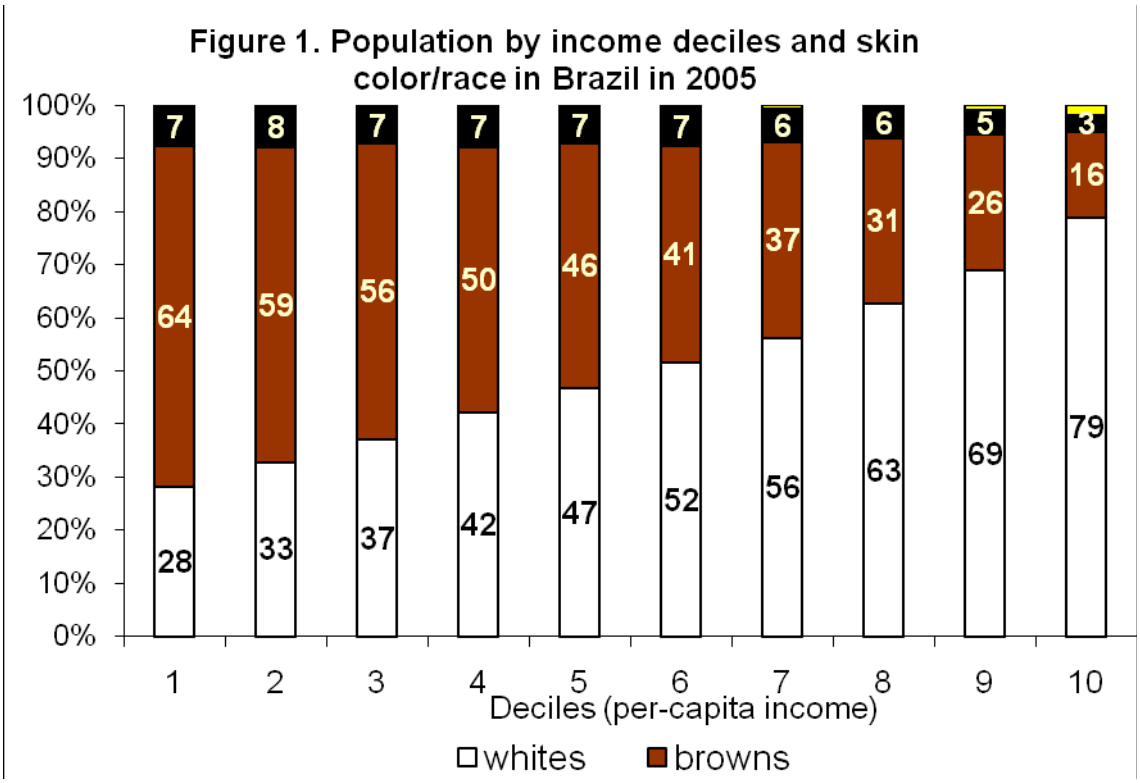
	Characteristics effect						Coefficients effect					
	2005	**%**	**1992** fixed (absolute) poverty line	**%**	**1992** relative poverty line	**%**	**2005**	**%**	**1992** fixed (absolute) poverty line	**%**	**1992** relative poverty line	**%**
RAW GAP	18.4 (0.14)	100	25.9 (0.18)	100	21.0 (0.17)	100	18.4 (0.14)	100	25.9 (0.18)	100	21.0 (0.17)	100
AGREGATE CHARACTERISTICS EFFECT	16.2 (0.13)	87.9	22.6 (0.25)	87.5	19.5 (0.22)	92.6	2.2 (0.20)	12.1	3.2 (0.35)	12.5	1.6 (0.29)	7.4
DETAILED:												
1. Geographic	3.2 (0.16)	17.3	4.9 (0.26)	18.8	4.6 (0.25)	21.8	0.8 (0.29)	4.1	0.5 (0.52)	2.1	0.4 (0.39)	1.7
1.1 State	3.1 (0.16)	17.1	4.6 (0.26)	17.7	4.3 (0.24)	20.5	0.5 (0.22)	3.0	0.2 (0.45)	0.8	0.2 (0.34)	1.1
1.2 Urvan vs. rural	0.0 (0.02)	0.2	0.3 (0.05)	1.1	0.3 (0.05)	1.3	0.2 (0.16)	1.2	0.3 (0.25)	1.3	0.1 (0.17)	0.6
2. Sociodemographic	4.4 (0.11)	24.0	6.6 (0.16)	25.6	5.1 (0.16)	24.4	0.4 (0.57)	2.3	-1.3 (1.05)	-5.1	-1.7 (0.80)	-7.9
2.1 Household type	0.0 (0.01)	0.0	0.1 (0.03)	0.3	0.1 (0.03)	0.3	0.3 (0.27)	1.9	0.4 (0.58)	1.5	0.2 (0.44)	0.7
2.2 Mobility	0.0 (0.05)	0.1	0.0 (0.09)	-0.1	0.0 (0.08)	0.0	0.2 (0.42)	1.0	-0.9 (0.76)	-3.5	-0.7 (0.55)	-3.1
2.3 Sex of head	0.0 (0.01)	0.3	0.1 (0.03)	0.3	0.1 (0.03)	0.3	-0.2 (0.14)	-0.9	0.0 (0.40)	-0.1	-0.3 (0.32)	-1.6
2.4 Age of head	0.2 (0.01)	1.3	0.0 (0.01)	0.0	0.0 (0.01)	-0.2	0.1 (0.14)	0.5	-0.1 (0.28)	-0.2	0.1 (0.21)	0.6
2.5 Number of dependents	4.1 (0.10)	22.4	6.5 (0.13)	25.1	5.1 (0.13)	24.0	0.0 (0.26)	-0.2	-0.7 (0.55)	-2.9	-0.9 (0.39)	-4.5
2.4.1 Aged 0–15 years	3.3 (0.08)	18.0	5.5 (0.13)	21.3	4.3 (0.12)	20.5	-0.1 (0.16)	-0.6	-0.2 (0.39)	-0.7	-0.6 (0.26)	-2.7
2.4.2 Aged 16–45 years	1.0 (0.04)	5.5	1.0 (0.04)	3.7	0.7 (0.059	3.5	0.1 (0.13)	0.6	-0.5 (0.29)	-2.0	-0.4 (0.22)	-1.8
2.4.3 Aged 46+ years	-0.2 (0.01)	-1.1	0.0 (0.01)	0.0	0.0 (0.01)	0.0	0.0 (0.06)	-0.2	0.0 (0.13)	-0.1	0.0 (0.09)	0.0
3. Education and labor activity	8.6 (0.17)	46.7	10.9 (0.21)	42.2	9.5 (0.21)	45.2	1.7 (0.70)	9.1	2.1 (1.06)	8.1	1.2 (0.81)	5.8
3.1. Family Head	5.7 (0.20)	31.1	8.1 (0.19)	31.3	6.9 (0.20)	32.6	1.3 (0.67)	6.8	2.4 (1.06)	9.5	1.6 (0.87)	7.4
3.1.1 Education of head	3.7 (0.20)	20.1	5.3 (0.20)	20.4	4.3 (0.22)	20.5	0.2 (0.26)	1.4	0.5 (0.48)	2.1	0.3 (0.38)	1.3
3.1.2 Labor activity of head	2.0 (0.11)	10.9	2.8 (0.11)	10.9	2.5 (0.11)	12.1	1.0 (0.59)	5.5	1.9 (0.90)	7.4	1.3 (0.72)	6.1
3.1.2.a Inactive	0.0 (0.01)	-0.1	0.0 (0.00)	0.0	0.0 (0.00)	0.0	0.0 (0.14)	-0.1	0.1 (0.16)	0.3	0.1 (0.12)	0.4
3.1.2.b Unemployed	0.1 (0.01)	0.7	0.0 (0.00)	0.2	0.0 (0.00)	0.2	0.0 (0.02)	-0.1	0.0 (0.04)	-0.2	-0.1 (0.03)	-0.2
3.1.2.c Employed (by occupation)	1.8 (0.11)	9.8	2.7 (0.11)	10.2	2.4 (0.11)	11.4	0.1 (0.23)	0.4	0.4 (0.26)	1.5	0.4 (0.21)	2.0
3.1.2.d Average weeks and weekly hours worked	0.1 (0.01)	0.5	0.1 (0.01)	0.4	0.1 (0.01)	0.5	1.0 (0.42)	5.2	1.5 (0.83)	5.8	0.8 (0.64)	4.0
3.2 Other members	2.9 (0.17)	15.6	2.8 (0.20)	10.9	2.7 (0.19)	12.6	0.4 (0.31)	2.3	-0.3 (0.50)	-1.3	-0.3 (0.47)	-1.6
3.2.1 Employed (by occupation, education, sex and age)	2.8 (0.17)	15.0	2.9 (0.20)	11.1	2.7 (0.19)	12.8	0.3 (0.41)	1.4	0.9 (0.52)	3.5	0.6 (0.41)	3.1
3.2.2 Average weeks and weekly hours worked	0.1 (0.01)	0.6	0.0 (0.00)	-0.1	0.0 (0.00)	-0.2	0.2 (0.26)	0.9	-1.2 (0.44)	-4.8	-1.0 (0.41)	-4.7
4. Nonlabor incomes: other nonworking family members	0.0 (0.03)	-0.1	0.2 (0.06)	0.8	0.2 (0.07)	1.1	0.1 (0.07)	0.7	-0.1 (0.13)	-0.5	-0.1 (0.13)	-0.7
5. Constant							-0.8 (1.01)	-4.1	2.0 (1.49)	7.9	1.8 (1.12)	8.5

Notes:

(i) Excluding rural areas of Rondônia, Acre, Amazonas, Roraima, Pará, and Amapá.

(ii) Linearized standard errors (Raw Gap), and Delta standard errors (aggregate and detailed effects) in parenthesis.

Source: Author's calculations using PNAD (1992 and 2005) data.



Note: Excluding rural areas of Rondônia, Acre, Amazonas, Roraima, Pará, and Amapá

Source: Author's calculations using PNAD (2005) data.

APPENDIX

Logit regressions of the probability of being poor in 1992 and 2005: estimated coefficients and statistical significance

	2005			1992			
				Relative poverty line		Fixed poverty line	
	Pooled sample	Whites	Afro-Brazilians	Whites	Afro-Brazilians	Whites	Afro-Brazilians
Indigenous	0.419**	-	-	-	-	-	-
Black+	0.343**	-	-	-	-	-	-
Asian	-0.055	-	-	-	-	-	-
Brown+	0.295**	-	-	-	-	-	-
Not classified	-0.933	-	-	-	-	-	-
Residence in north: Rondônia	0.06	0.460**	-0.142	0.410*	-0.015	0.13	0.052
Residence in north: Acre	0.162	0.368	0.072	-0.082	-0.064	-0.274	-0.039
Residence in north: Amazonas	-0.450**	-0.032	-0.603**	0.348*	0.102	0.460**	0.182
Residence in north: Roraima	0.258	0.719**	0.116	-0.815	-1.522**	-1.315**	-1.162**
Residence in north: Pará	0.095	0.285**	-0.008	0.197	0.003	0.127	-0.073
Residence in north: Amapá	-0.505**	-0.306	-0.609**	-0.23	-1.189**	-0.274	-0.984**
Residence in north: Tocantins	0.564**	0.731**	0.477**	0.253	0.338**	0.325	0.404**
Residence in northeast: Maranhão	1.078**	1.091**	1.020**	0.560**	0.529**	0.672**	0.588**
Residence in northeast: Piauí	0.971**	0.879**	0.950**	0.796**	0.916**	1.061**	0.968**
Residence in northeast: Ceará	1.196**	1.422**	1.065**	0.971**	0.699**	0.812**	0.663**
Residence in northeast: Rio Grande do N.	0.722**	0.981**	0.572**	0.944**	0.828**	0.977**	1.008**
Residence in northeast: Paraíba	0.799**	0.958**	0.705**	1.134**	0.912**	1.225**	0.838**
Residence in northeast: Pernambuco	0.959**	1.161**	0.841**	0.796**	0.429**	0.798**	0.551**
Residence in northeast: Alagoas	0.805**	0.896**	0.754**	0.597**	0.204	0.405**	0.306**
Residence in northeast: Sergipe	0.754**	0.965**	0.647**	0.483**	0.544**	0.478**	0.549**
Residence in northeast: Bahia	0.612**	0.819**	0.523**	0.446**	0.194**	0.333**	0.188**
Residence in southeast: Espírito Santo	-0.162	-0.116	-0.191	0.221	-0.08	0.285**	0.154
Residence in southeast: Rio de Janeiro	-0.527**	-0.482**	-0.551**	-0.514**	-0.615**	-0.536**	-0.573**
Residence in southeast: São Paulo	-0.791**	-0.728**	-0.790**	-0.854**	-1.120**	-0.832**	-0.982**
Residence in south: Paraná	-0.245**	-0.155*	-0.235**	0.03	-0.151	-0.007	-0.038
Residence in south: Santa Catarina	-1.020**	-0.991**	-0.765**	-0.573**	-0.37	-0.585**	-0.333
Residence in south: Rio Grande do S.	-0.451**	-0.328**	-0.511**	-0.357**	-0.556**	-0.423**	-0.476**
Residence in centre-west: Mato Grosso do S.	-0.186**	-0.058	-0.254**	0.161	-0.345**	0.108	-0.235*
Residence in centre-west: Mato Grosso	-0.677**	-0.708**	-0.712**	-0.159	-0.416**	-0.206	-0.331**
Residence in centre-west: Goiás	-0.271**	-0.124	-0.361**	-0.068	-0.312**	-0.028	-0.277**
Residence in centre-west: Distrito Federal	-0.368**	-0.273*	-0.421**	-0.485**	-0.482**	-0.360**	-0.484**
Residence in urban area	-0.130**	-0.203**	-0.087*	-0.378**	-0.313**	-0.384**	-0.273**
Couple	0.476**	0.319**	0.554**	0.483**	0.922**	0.612**	0.804**
Single mother	0.562**	0.429**	0.625**	0.781**	1.077**	0.842**	1.016**
Other type of family	0.306**	0.14	0.386**	0.628**	0.728**	0.677**	0.662**
Multifamily household	-0.342**	-0.316**	-0.357**	-0.496**	-0.130*	-0.287**	-0.182**
Head moved from the same state	-0.165**	-0.162**	-0.168**	-0.126**	-0.113**	-0.121**	-0.154**
Head moved from north	-0.136	0.02	-0.193	-0.450*	-0.122	-0.597**	-0.162
Head moved from northeast	-0.163**	-0.046	-0.239**	-0.083	-0.222**	-0.1	-0.260**
Head moved from southeast	-0.191**	-0.182**	-0.217**	-0.088	-0.154*	-0.11	-0.152**
Head moved from south	-0.259**	-0.256**	-0.256*	-0.113	-0.337**	-0.117	-0.147
Head moved from centre-west	-0.540**	-0.564**	-0.532**	-0.472**	-0.215	-0.297	-0.195
Head moved from abroad	-0.327	-0.233	-0.311	-0.04	0.53	-0.265	0.029
Female household head	0.211**	0.129	0.255**	0.076	0.226**	0.229**	0.234**
Head aged 25–55 years	-0.696**	-0.763**	-0.660**	-0.421**	-0.332**	-0.541**	-0.511**
Head aged 56+ years	-2.106**	-2.284**	-2.020**	-1.281**	-1.154**	-1.241**	-1.087**
Head with 1–3 years of education	0.146**	0.084	0.175**	-0.063	0.05	-0.063	0.032

Head with 4–7 years of education	-0.261**	-0.344**	-0.212**	-0.502**	-0.315**	-0.492**	-0.338**
Head with 8–10 years of education	-0.726**	-0.826**	-0.661**	-1.022**	-0.835**	-1.068**	-0.869**
Head with 11–14 years of education	-1.476**	-1.675**	-1.335**	-1.881**	-1.620**	-1.894**	-1.773**
Head with 15+ years of education	-3.114**	-2.996**	-3.540**	-2.785**	-3.043**	-3.134**	-3.258**
Head literate	-0.368**	-0.349**	-0.392**	-0.357**	-0.343**	-0.459**	-0.368**
Head inactive	-1.112**	-1.038**	-1.124**	-1.176**	-0.950**	-1.348**	-1.100**
Head unemployed	0.534**	0.678**	0.461**	0.728**	0.537**	0.371**	0.382**
Head: informal employee in domestic service	-0.143	0.182	-0.310**	-0.494**	-0.254*	-0.456**	-0.207
Head: informal employee in other industries	-0.734**	-0.730**	-0.726**	-0.977**	-0.712**	-0.938**	-0.706**
Head: formal employee in agriculture	-1.069**	-0.891**	-1.171**	-0.981**	-0.935**	-0.766**	-0.592**
Head: formal employee in domestic service	-0.814**	-0.698**	-0.870**	-0.328	-0.719**	-0.738**	-1.000**
Head: formal employee in another industry (manager or professional in private sector)	-2.780**	-3.046**	-2.590**	-3.119**	-2.458**	-2.737**	-2.318**
Head: formal employee in another industry (other in private sector)	-1.598**	-1.512**	-1.643**	-1.997**	-1.825**	-1.726**	-1.568**
Head: formal employee in another industry (manager or professional in public sector)	-4.981**	-5.052**	-4.843**	-2.158**	-1.700**	-2.195**	-1.697**
Head: formal employee in another industry (other in public sector)	-1.840**	-1.784**	-1.878**	-1.906**	-1.656**	-1.745**	-1.605**
Head: self-employed in agriculture	-0.219**	-0.181	-0.221**	-0.668**	-0.431**	-0.773**	-0.437**
Head: self-employed in another industry	-1.018**	-0.966**	-1.039**	-1.594**	-1.298**	-1.546**	-1.207**
Head: employer	-2.488**	-2.556**	-2.409**	-2.720**	-2.600**	-2.904**	-2.711**
Head: unpaid/other	-0.298**	-0.073	-0.427**	-0.207	-0.418**	-0.665**	-0.573**
Hours worked by head	-0.019**	-0.022**	-0.017**	-0.018**	-0.015**	-0.016**	-0.012**
No. of dependents aged 0–9 years	0.993**	1.005**	0.986**	0.190**	0.203**	0.194**	0.211**
No. of dependents aged 10–15 years	0.805**	0.820**	0.800**	0.569**	0.505**	0.601**	0.578**
No. of dependents aged 16–45 years	0.750**	0.726**	0.765**	0.574**	0.496**	0.633**	0.562**
No. of dependents aged 46–64 years	1.251**	1.276**	1.244**	0.950**	0.931**	0.910**	0.879**
No. of dependents aged 65+ years	0.997**	1.108**	0.938**	0.531**	0.575**	0.434**	0.473**
No. of employed aged 10–15 years (0–3)	0.334**	0.151	0.426**	0.279**	0.161**	0.180**	0.233**
No. of employed aged 10–15 years (4–7)	0.140**	-0.073	0.267**	-0.264**	-0.232**	-0.201**	-0.07
No. of employed aged 10–15 years (8+)	0.04	-0.099	0.175	0.397	-0.516	0.133	-0.571
No. of employed aged 16–45 years (0–3)	-0.018	0.056	-0.043	-0.256**	-0.275**	-0.229**	-0.253**
No. of employed aged 16–45 years (4–7)	-0.287**	-0.316**	-0.268**	-0.373**	-0.509**	-0.411**	-0.397**
No. of employed aged 16–45 years (8–10)	-0.324**	-0.279**	-0.345**	-0.500**	-0.740**	-0.704**	-0.589**
No. of employed aged 16–45 years (11+)	-0.809**	-0.821**	-0.795**	-0.993**	-1.216**	-1.141**	-1.038**
No. of employed aged 46+ years (0–3)	-0.334**	-0.384**	-0.317**	-0.281**	-0.331**	-0.276**	-0.206**
No. of employed aged 46+ years (4–7)	-0.467**	-0.706**	-0.278**	-0.531**	-0.708**	-0.322**	-0.425**
No. of employed aged 46+ years (8–10)	-0.547**	-0.206	-0.746**	-2.391**	-1.005*	-1.707**	-0.701*
No. of employed aged 46+ years (11+)	-1.430**	-1.151**	-1.632**	-1.046**	-2.213**	-1.533**	-2.006**
No. of informal employees in agriculture	-0.155**	-0.139	-0.165**	-0.166**	-0.023	-0.049	0.109*
No. of informal employees in domestic service	0.101*	0.066	0.101	-0.035	0.054	0.198**	0.233**
No. of informal employees in another industry	-0.446**	-0.487**	-0.444**	-0.311**	-0.124**	0.017	0.079
No. of formal employees in agriculture	-1.551**	-1.413**	-1.585**	-1.306**	-0.888**	-1.132**	-0.781**
No. of formal employees in domestic service	-1.143**	-1.170**	-1.159**	-0.848**	-1.332**	-0.460**	-0.674**
No. of formal employees in another industry (managers or professionals in private sector)	-2.874**	-3.159**	-2.522**	-1.918**	-1.615**	-1.498**	-1.467**
No. of formal employees in another industry (others in private sector)	-1.431**	-1.475**	-1.437**	-1.370**	-1.152**	-0.863**	-0.694**
No. of formal employees in another industry (managesr or professionals in public sector)	-2.680**	-3.124**	-2.480**	-0.521**	-0.607**	-0.291*	-0.332**
No. of formal employees in another industry (others in public sector)	-1.640**	-1.761**	-1.606**	-0.938**	-0.614**	-0.685**	-0.444**
No. of self-employed in agriculture	-0.099	-0.082	-0.108	-0.414**	-0.466**	-0.264**	-0.330**
No. of self-employed in another industry	-0.207**	-0.257**	-0.203**	-0.315**	-0.175**	-0.166**	-0.124*
No. of employers	-1.923**	-2.059**	-1.813**	-3.360**	-2.277**	-2.636**	-2.352**
No. of females employed	0.241**	0.285**	0.221**	0.171**	0.335**	0.285**	0.219**
Average weekly hours worked	-0.013**	-0.014**	-0.013**	-0.005**	-0.012**	-0.005**	-0.010**
No. of other income receivers (0–3)	-0.803**	-0.991**	-0.702**	-0.733**	-0.949**	-0.508**	-0.492**

No. of other income receivers (4–7)	-0.057	-0.343**	0.098	-0.425*	-0.520**	-0.311*	-0.255
No. of other income receivers (7–10)	-0.441**	-0.707**	-0.298**	0.03	-0.514	-0.085	-0.519
No. of other income receivers (11+)	-1.007**	-1.243**	-0.865**	-0.251	-1.285**	-0.247	-1.037**
No. of other female income receivers	0.527**	0.735**	0.419**	-0.390*	-0.189	-0.188	-0.157
Constant	0.113	0.431**	0.228*	0.425**	0.031	0.973**	0.661**
No. of unweighted observations	388,653	180,078	206,259	159,314	147,706	159,314	147,706
Log-likelihood	-100,970	-36,033	-66,215	-38,838	-53,724	-49,316	-57,408
Pseudo R^2	52.3	51.5	49.3	46.3	45.2	44.7	43.9

Notes:
Numbers in parenthesis (first column) indicate years of schooling
[+] Colour coefficients between blacks and browns do not differ significantly at 10%.
* Significant at 10%, ** significant at 5% (with robust standard errors, individuals clustering across households).
Reference: Lone male aged 16–24 years with no formal education, illiterate, living in rural Minas Gerais, employed in agriculture, and a non-migrant.
Source: Author's calculations using PNAD (1992 and 2005) data.

[1] This has been the case since 2004, and as a consequence, observations from the rural population of six states in the Amazonian area in the north of Brazil (Rondônia, Acre, Amazonas, Roraima, Pará, and Amapá) need to be excluded from the 2005 survey in order to facilitate comparability with 1992.

[2] Telles (2002), among others, supports this view, arguing that the white versus non-white distinction is less ambiguous. After comparing the consistency in a specific survey between interviewer and respondent categorizations, he showed that racial classification between black and brown is more influenced by characteristics such as education, gender, age, and local racial composition.

[3] In a similar way, Ferreira *et al.* (2006) used a 2004 threshold of R$ 100 in their study, which was the initial limit of the program. Several other studies have set the threshold at half the minimum wage (or a quarter of this to define extreme poverty).

[4] Following the parameterization of Buhman *et al.* (1988).

[5] Comparing data between 1992 and 2005 is not straightforward, due to the need to restrict the 2005 sample geographically, as already mentioned, and to construct employment variables based on different classifications for occupations.

[6] I adjusted the 1992 income using the INPC time deflator reported in Ferreira *et al.* (2006).

[7] See Oaxaca (1973) and Blinder (1973).

[8] See, for example, Cappellari and Jenkins (2004) for a justification of this.

[9] Even though the endogeneity problem is expected to be less relevant when variables are specified at the household level, correlation between unobservables and some of the household decisions (like those allocating labor supply) cannot be fully ruled out. Further, in some cases there might be double causality; for example, in the case of the number of dependent children in the household. A large number of children directly affects the probability of being poor by increasing household needs (number of household members) but not providing additional income. However, this characteristic could also be rather a consequence of living in a poor, less-educated household.

[10] Note that for the sake of robustness the analysis was repeated with the alternative assumption, with no substantial difference in results.

[11] See, for instance, Gang *et al.* (2006) and Bhaumik *et al.* (2006) for the analysis of intergroup poverty rates in India and Kosovo; and Biewen and Jenkins (2005) and Quintano and D'Agostino (2006) who examined inter-country differences in poverty levels. A similar decomposition is found in other (nonlinear) contexts: Gomulka and Stern (1990) analyzed the changes in the employment of married women; Ham *et al.* (1998) analyzed inter-country differences in the duration of unemployment; Farlie (1999, 2005) analyzed the racial discrepancies in the transition rate into self-employment and in computer ownership; Nielsen (1998, 2000) analyzed the gender discrepancy in formal sector employment and child labour incidence; Bevelander and Nielsen (2000) analyzed the employment success of immigrants; and Gang et al. (2002) analyzed attitudes toward foreigners in the European Union. Alternative decomposition strategies of the aggregate effects can be found in Borooah (2005), Borooah and Iyer (2005a,b) and Even and Macpherson (1990, 1993).

[12] This approach was used by, among others, Gang *et al.* (2006), Bhaumik *et al.* (2006), and Gang *et al.* (2002).

[13] An alternative linearization strategy can be found in Doiron and Riddell (1994).

[14] Sequential approaches have been applied to, for instance, detailed decompositions of both effects (Gomulka and Stern, 1990) and of only the characteristics effect (Farlie, 1999, 2005; Ham *et al.*, 1998). The latter involves computing an average of all possible permutations of characteristics in order to override path dependency.

[15] Sequential approaches require a matching assumption to be imposed. For instance, Fairlie (1999, 2005) drew a random subsample from the largest group that was equal in size to the smallest group. Both groups of observations were ranked according to their predicted probabilities and matched by their respective rankings when computing the change in the characteristics effect. The final estimate was produced by computing the mean effect after repeating this exercise a large number of times.

[16] Jones (1983) pointed out the problem of identifying the contribution of the intercept using the approach of Blinder (1973) in the presence of a set of dummy variables. Oaxaca and Ransom (1999) showed, more generally, that conventional decompositions cannot identify the separate contribution of dummy variables because it is only possible to estimate the *relative* effect of a dummy variable.

However, Gelbach (2002) argued that the problem is not one of identification, but of population heterogeneity in parameter estimates.

[17] However, as Oaxaca and Ransom (1999) stressed, the combined estimated contributions of all sets of dummy variables — including the constant term — to the overall coefficients effect are invariant to the reference group.

[18] Fairlie (1999, 2005) and Ham *et al.* (1998) are good examples of this in the nonlinear case.

[19] A similar identification problem affects affine transformations of continuous regressors that involve a location parameter. As Yun (2005a) pointed out, unlike categorical variables, the problem related to a continuous variable cannot be resolved because there are infinitely many transformations. Therefore, one has to rely on specifications that make sense and are widely accepted in the literature.

[20] Ferreira et al. (2003) obtained non-significant coefficients for race dummies, but this was probably due to their having introduced several wealth-related variables in the right-hand side of the regression, such as the availability of electricity and piped water, and housing status.

[21] Normalized regressions coefficients and summary statistics are available in an additional Appendix in the Journal's website. Alternatively, applying the regression separately to each coloured group (blacks and browns) and using our methodology to explain the discrepancy between their poverty rates (6.6%) revealed that if browns had the same characteristics as blacks, the poverty rate after conditioning by characteristics would be almost zero; that is, all the difference can be explained by the characteristics effect.

[22] Here I discuss the effect of sets of characteristics while the complete list of individual detailed effects is reported in the Appendix. For robustness purposes, the analysis was done changing the underlying equivalent scale (using the square root of household size to adjust incomes) and a higher poverty line. The most noteworthy difference in the former case was a lower contribution from the number of children and young adults, while there was no outstanding difference in the latter.

[23] However, the reduction was proportionally higher for whites (from 24.8 to 14.5 percent, 42 percent of the reduction) than for Afro-Brazilians (from 50.1 to 32.8 percent, 35 percent of the reduction).

[24] This is because the decrease in poverty was mainly due to (modest) economic growth, combined with a small decrease in inequalities (Ferreira *et al.*, 2006).

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