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Earnings Inequality Within and Across Gender, Racial, and Ethnic Groups in Four Latin American Countries

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Abstract

Latin American countries are generally characterized as displaying high income and earnings inequality overall along with high inequality by gender, race, and ethnicity. However, the latter phenomenon is not a major contributor to the former phenomenon. Using household survey data from four Latin American countries (Bolivia, Brazil, Guatemala, and Guyana) for which stratification by race or ethnicity is possible, this paper demonstrates (using Theil index decompositions as well as Gini indices, and 90/10 and 50/10 percentile comparisons) that within-group earnings inequality rather than between-group earnings inequality is the main contributor to overall earnings inequality. Simulations in which the relatively disadvantaged gender and/or racial/ethnic group is treated as if it were the relatively advantaged group tend to reduce overall earnings inequality measures only slightly and in some cases have the effect of increasing earnings inequality measures.

This paper—a product of the Social Protection Division, Latin America and Caribbean Region, Human Development Department—is part of a larger effort in the department to identify policy to improve the situation of the most vulnerable. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The author may be contacted at Wcunningham@worldbank.org.

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Latin American countries are generally characterized as exhibiting both high wage and earnings inequality[1]—and significant gender,[2] racial, and ethnic-related inequality.[3] Hence an interesting question to ask is: To what extent are these two features interrelated?

In this paper we address this question by considering how greater equality by gender and race/ethnicity in distribution of labor earnings would affect overall labor earnings inequality. Using household survey data from four Latin American countries for which it is possible to calculate earnings separately by race (Brazil and Guyana) or ethnicity (Bolivia and Guatemala), we calculate a number of inequality indexes, both overall and separately by race/ethnicity and gender. We show that there is significant gender and intraracial/ethnic group earnings inequality as well as substantial overall earnings inequality.

We then recalculate the overall labor earnings inequality index under a series of assumptions that increasingly treat members of the worse-off gender and/or racial/ethnic group as if they were members of the better-off group. We show, using a relatively new empirical methodology developed by Bourgignon, Ferreira and Lustig (1998),[4] that these steps do not have a large effect in reducing overall inequality measures, and indeed can increase inequality measures in some cases. This is not surprising, given the high levels of intragroup inequality that we have shown and the many unobservable factors that affect wages. However, this may be surprising to those who have not seen these intragroup measures previously.

[1] There are many overall inequality studies that consider all or part of the Latin American and Caribbean region (LAC), and some also compare LAC to all or part of the rest of the world. See Psacharopoulos et al. (1995), Londoño and Székely (1997), Inter-American Development Bank (1998), Morley (2001), Székely and Hilgert (1999, 2007), De Ferranti et al. (2004) World Bank (2004), and Medrano, Sanhueza, and Contreras (2006) for overviews of the inequality discussion in Latin America, and Deininger and Squire (1996) for the world comparison. Studies that consider the intergenerational transmission of inequality in LAC include Behrman, Gaviria and Székely (2001), which finds that LA is less mobile than the US and that mobility is associated with education; and Barros and Lam (1993) and Lam (1999), both of which consider intergenerational transmission of educational inequality in Brazil.
[2] In terms of gender analysis in the LAC region, Tzannatos and Psacharopoulos (1992) find that across the region, women's earnings and labor force participation are consistently lower than men's. Also see Saavedra (2001), who looks at female wage inequality in LAC, Brown, Pagga, and Oreggia (1999), on Mexico, Esquivel and Paz (2003) on Argentina, and Pagan (2002) on Guatemala.
[3] LAC studies on race and/or ethnicity are scarce, with country-level studies of Brazil comprising the bulk of the research. Notable studies on indigenous groups include Psacharopoulos and Patrinos (1994) and Hall and Patrinos (2006), both of which conclude that indigenous peoples are systematically pooer than non-indigenous peoples.
[4] Other studies using this type of methodology include Bouillon, Legovini, and Lustig (1998), Ferreira and Paes de Barros (1999), Bravo, Contreras, Rau, and Urzua (2000), Bourguignon, Fournier, and Gurgand (2001), Bourgignon, Ferreira, and Leite (2002), Ferreira and Leite (2005), and Gasparini, Marchionni, and Escudero (2005). Bourguignon and Spadaro (2006) discuss the use of this methodology to evaluate social policies.

Hence this paper both contributes new empirical results from these so-far rarely utilized household surveys,[5] and presents a new angle regarding the causes of inequality and potential consequences of gender and/or race/ethnicity-related anti-discrimination policy measures.

Below we first present the baseline inequality measures for the four countries. We also present conventional Blinder-Oaxaca decompositions to indicate how much of earnings differences by race/ethnicity/gender is related to differences in characteristics between the groups and how much is related to differences in treatment.[6]

We then describe and implement an extension to the Blinder-Oaxaca methodology, developed by Bourguignon *et al.* (1998) and implemented in Bourguignon *et al.* (2002). Herein we consider how various characteristics are generated and simulate these processes before simulating or decomposing earnings. For example, under the assumption that educational attainment is generated differently by race/ethnicity/gender group, we allow education to be generated for the worse-off group by the process associated with the better-off group, and then use predicted education in place of actual education in simulating earnings for the worse-off group. To our knowledge, we are the first to use this technique to consider within-country differences between race/ethnicity/gender groups.[7]

We compare our actual earnings inequality measures to inequality measures calculated using the simulated earnings data for the worse-off group. We show that this simulation has little effect on overall inequality in the majority of cases. Instead, within-group inequality persists and drives the over-all inequality. We show that this finding holds up for per capita household earnings measures as well as for individual earnings, so that household structure, and the income sharing that may occur within households, does not mitigate this result. In the conclusion, we consider what implications our findings have regarding the efficacy of anti-discrimination policy and affirmative action policies in reducing overall earnings inequality.

[5] See Székely and Hilgert (2007) for a discussion of the problems with using LAC household surveys.
[6] This is the standard methodology used to understand wage differentials; when applied to LAC data, studies typically find that the majority of the wage gap between either gender or racial categories is due to differences in characteristics—see Garcia-Aracil and Winter (2006) on Ecuador, Hall and Patrinos (2006) for a range of countries, Patrinos (1997) on Guatemala, MacIsaac and Patrinos (1995) on Peru.
[7] This statement holds as of the date of our original working paper, August 2003.

Patterns of earnings inequality

While it is quite common to find commentaries mentioning differences in the extent of inequality by gender,[8] race, and ethnicity[9] in Latin America, along with decrying the overall extent of inequality, it is far less common to see a formal analysis of to what extent the former is responsible, or in any way linked, to the latter. Psacharapoulos and Patrinos (1994) have tackled the estimation of racially and/or ethnically separate earnings equations for Latin American countries and attempted to measure the contribution of racial and ethnic differences to earnings differences. In addition, in the earnings equation decomposition literature, it is rare to see any reaggregation of the data into a measure of overall earnings inequality in order to be able to see how various counterfactual calculations might affect such a measure.

It is particularly difficult to study the differential patterns of earnings inequality by race/ethnicity across all of the Latin American and Caribbean countries because many Censuses and labor force or household surveys do not ask questions delineating race (Florenz, Medina, and Urrea 2001). We surveyed the most recent available household surveys for these countries at the time our project began in 2003, and found four in which there is both sufficient coding to be able to separate out "dominant" and "disadvantaged" groups by race/ethnicity and sufficient sample sizes to be able to estimate separate earnings regressions by gender and race/ethnicity. These are the 1999 *Encuesta Continua de Hogares* for Bolivia, the 1996 *Pesquisa Nacional de Amostra da Domicilio* for Brazil, the 2000 *Encuesta Nacional sobre Condiciones de Vida* for Guatemala, and the 1999 *Survey of Living Conditions* for Guyana. These countries all have either sizable Afro-descendant or Indigenous populations, with Brazil and Guyana having the two highest percentage Afro-descendant populations (44.7% and 42.6% respectively) and Bolivia and Guatemala having the two largest reported indigenous populations (71% and 66% respectively) in Central and South America. Guyana is also interesting in that the "dominant" population is of South Indian background (Indo-origin, in our terminology below) rather than white background (in contrast to the other three countries). So while we use the term "white" as shorthand to refer

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[8] Women still lag behind men in most indicators of well-being — wage gaps, control over resources, voice, health care (Cunningham et al, 2004) — but there are increasingly noted trends of disadvantage among men, including higher death rates, alcoholism, and suicides than women, as well as particularly in LAC countries a reduction in their rate of higher educational attainment (Jacobsen 2006).

[9] Sociologists have theorized that racial or ethnic inequalities are a result of a history of power relations that create an unlevel playing field through setting up a situation wherein endowments, opportunities, and/or expectations differ by demographic gruop (Baiocchi 2003). These theories are becoming salient as ethnic and racial groups are

to the dominant group in each society, the dominant group in Guyana is not actually white, and in each society the nondominant group varies in its composition (ranging from more Afro-descendant dominated in Brazil and Guyana, to indigenous group-dominated in Bolivia and Guatemala). Because these countries have the largest non-white populations in Latin America, if the main source of inequality was between groups, then equal treatment would have a large impact on overall inequality measured for the country. However, these countries may also not have as much inequality between groups because they have such large non-white populations, and therefore it may be worth in the future also investigating other countries with smaller non-white populations (e.g., Chile) to see if they are more marginalized, once such data become available.

Table 1 displays various measures of hourly earnings inequality for these four countries, overall and by gender-racial/ethnic group. We utilize the Theil (1) and (0) indexes, the Gini index, and ratios of 90/10 and 50/10 points in the income distribution to describe earnings inequality.[10] We choose these five inequality indices as ones that are well known and often calculated; thus they can be compared to those found in other countries and/or for other time periods. In addition, the indexes give us different ways of thinking about inequality, with the 90/10 focusing our attention on the tails of the distribution, the 50/10 focusing on the lower half of the distribution, and the other three indices summarizing the full distribution. While the Gini index is perhaps the best known, the Theil family of indices are of particular interest to us because they can be decomposed into within and between group components, as will be done below.

We see that, with the notable exception of Guyana, earnings inequality is high measured by any of these standards. But, strikingly, inequality is not only high overall, but also comparably high within each of the four gender-racial/ethnic groups. Also, no one racial-gender or ethnic-gender group is the most unequal consistently across the sample. While the most unequal wage distribution in Brazil is that of white men, Indo-women have the largest inequality in earnings in Guyana and indigenous women tend to have the highest earnings inequality in Bolivia and Guatemala.

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increasingly reshaping their cultures and raising their voices for equal rights and a greater share of the opportunities in their countries (Arocha 1998).

[10] For the formal definitions of the Gini, Theil (1), and Theil (0) indexes, as well as a discussion of index decomposition, see Litchfield (1999), Cowell (2000), or Cowell (2005).

Table 2 shows the results from standard Oaxaca-Blinder decompositions of log earnings, comparing in turn men and women within race, whites and nonwhites within gender, and white men to nonwhite women.[11] Women tend to receive a relatively higher payoff from economic attainment than do men (with the notable exception of white women in Guatemala).

Table 2 shows that Guyana has noticeably small wage differentials by race/ethnicity, while Bolivia has the smallest wage differential by gender within the dominant group and Guatemala has the widest gender differentials. Notably, while racial/ethnic differences (controlling for gender) have a large characteristics component,[12] gender differences (controlling for race/ethnicity) have a large differences-in-treatment component. Indeed, women's characteristics in both Bolivia and Brazil (and in Guyana for Afro-origin women) would contribute to lowered earnings inequality if it were not for the offsetting effects of differences in coefficients. While the "endowed" differences between races/ethnicities are by region and education, the differences between men and women are primarily in employment position. The difference in wages by race/ethnicity that can be attributed to returns to endowments (i.e., the differences in coefficients) is primarily due to education. The returns to education are also important for explaining the gender wage gap, but returns to other factors also emerge as important.

A focus on decompositions such as provided in Table 2 makes it appear as though earnings differences would decline notably if differences in treatment (i.e., differences in coefficients) were eradicated, and also that race/ethnicity differences would diminish substantially in all countries save Guyana if differences in characteristics were narrowed.

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[11] This paper's technical appendix, available from this World Bank website, contains the full regression results used to create these decompositions, including the first stage multinomial logit results and the final stage OLS earnings regressions for the multi-stage simulation described below. The surveys vary in sample size, availability of variables, and goodness of fit of the earnings equations. While the four country surveys used herein were chosen in part because they had relatively good and also relatively similar data available, the specifications are not identical due to data limitations and coding differences. However, some standard patterns of returns occur across all four countries, namely the constancy of positive returns to higher educational attainment, and a traditional quadratic relationship between age and earnings that is remarkably similar across the four countries. There are positive relationships to earnings of being in urban rather than rural settings, and having employment in a relatively more formal sector.

[12] This has been found in other studies of Latin American data, including MacIsaac and Patrinos (1995), using Peruvian data, which finds fifty to seventy percent of the log earnings gap between indigenous and nonindigenous men due to differences in characteristics; Patrinos, Velez, and Psacharopoulos (1994), which finds seventy-eight percent of the difference between Spanish and Guarani speakers due to differences in characteristics; and Psacharopoulos and Patrinos (1994), although Patrinos (1997) points out variation in the proportion attributable to characteristics among the various ethnic groups within Guatemala. Our result is partly consistent with Soares (2000),

However, neither of these measures necessarily translates into substantially reduced overall earnings inequality. Oaxaca-Blinder decompositions are decompositions at the mean characteristic values for the sample and do not give good insight about the full differential distributions of characteristic values in each subsample.[13] Differences in characteristic distributions within each subsample generate the within subsample earnings differences that we observe in Table 1. Therefore, even if mean characteristics were equalized within each group as well as treatment of those characteristics, substantial overall earnings inequality could still exist in the society because of the spread in characteristics—and potentially in returns to characteristics—within groups. In the next section we consider how to simulate both more equal characteristic distributions and more equal treatment and how these simulations would affect measures of overall earnings inequality.

Simulating more equal treatment to assess its effects on overall earnings inequality

In this section we move beyond the simple Oaxaca-Blinder decomposition framework by simulating wages using firstly the Oaxaca-Blinder framework in which only returns are equalized, and secondly by using an expanded framework in which both returns and the processes generating some of the underlying characteristics are equalized. We then compare the actual earnings inequality indexes to the one calculated for the distributions of simulated wages under both of these frameworks.

Operationally, the expanded framework consists of allowing some of the variables in the earnings equation to be determined by earlier processes that are also estimated separately by group. There is certainly evidence, both in the Latin American context and for other regions and countries, that earlier processes affect outcomes that then affect earnings. For example, Patrinos and Psacharopoulos (1997) find that family background has an impact on educational attainment and grade repetition. And it is certainly the case that observers believe that these processes have severe effects that differ by group; witness Tzannatos (1999, p. 551): "To break the vicious circle of women's low initial human capital endowments and inferior labor market outcomes compared

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who, using Brazilian data, finds the difference between men by race to be mainly driven by characteristics, though among women by race it is driven mainly by differences in treatment.

[13] Other decompositions can be performed which do consider the variance in outcomes across the earnings distribution; for instance see Yun (2006), who creates a valuable extension on the more widely known Juhn, Murphy, and Pierce (1993) method; quantile regression analysis is another strategy. We choose to focus the paper

to men's, the paper proposes greater access of girls to education and of women to training, enforceable equal pay and equal employment opportunities legislation, a taxation and benefits structure that treats reproduction as an economic activity and women as equal partners within households, and a better accounting of women's work to include invisible production."

Following the Bourguignon *et al*. (2002) method, we simulate conditional distributions for occupational choice, education, fertility (for women only), and non-labor income. In addition, as it is possible that an individual observed in an occupational status without wages (i.e., self-employed and non-employed persons) needs to be simulated as being in another occupational status, the random error terms are drawn for the simulations from the counterfactual distribution of error terms.[14] Bourguignon *et al*. apply their method to considering differences in household income distribution across countries; however, it is readily modifiable to considering differences in household income distribution—or individual income or earnings distributions—across demographic groups within a country.

To summarize the approach in equation format, consider the two equations for earnings Y for (subscript) groups 1 and 2, with each vector Y expressed as a function of matrices of explanatory variables X and Z, where the Z-variables are endogenous, and are functions of the matrix of explanatory variables H (which may contain a subset of the variables in X); all subscripts refer to groups 1 and 2, and an implicit dimensionality equal to each group's sample size:

$$\begin{cases} Y_1 = X_1\beta_1 + Z_1\gamma_1 + \mu_1 \\ Y_2 = X_2\beta_2 + Z_2\gamma_2 + \mu_2 \end{cases}$$

$$\begin{cases} Z_1 = H_1\delta_1 + \varepsilon_1 \\ Z_2 = H_2\delta_2 + \varepsilon_2 \end{cases}$$

Where β, γ, and δ are coefficients to be estimated and μ and ε are random error terms.

Then once β, γ, and δ are estimated, an estimate of Z_2 can be constructed for each individual, and then of Y_2 under the situation where members of group 2 are treated as if they are members of group 1 (although still subject to the error term variance experienced by group 2):

on our inequality index simulation results and consider the Oaxaca-Blinder method as a benchmark rather than explore multiple decompositions.

$$\hat{Z}_2 = H_2\hat{\delta}_1 + \hat{e}_2$$
$$\hat{Y}_2 = X_2\hat{\beta}_1 + \hat{Z}_2\hat{\gamma}_1 + \hat{\mu}_2$$

Note that if Z contains no elements, if X_2 is set to the mean values for group 2, and $\hat{\mu}_2$ is set to zero, then $\hat{Y}_2$ corresponds to the standard estimate of what the mean of Y_2 would be if group 2 members were treated like group 1 members, an estimate that is generally used to perform a Oaxaca-Blinder decomposition. Otherwise, this method should tend to bring the simulated earnings distribution for group 2 "closer" to the earnings distribution for group 1.

It is therefore of interest to see how much allowing the past to be changed, i.e., allowing educational attainment, number of children born, and occupational sector for group 2 to be determined by processes that are the same as group 1 faces, changes the current earnings outcome for group 2. If even this additional movement towards equalization of outcomes does not reduce earnings inequality significantly for the country as a whole, then it is difficult to make the case that earnings inequality is determined in any significant part by differences in treatment between the groups.

Our estimation of Z proceeds in three steps, as some actions are considered prior to others: we consider that first education is obtained, then children born, then (current) occupational sector entered. The first step in this process is to estimate education level for members of group 1 as a function of age, mother's level of schooling (when available),[15] and region of birth (when available; alternatively we proxy it using current geographic location). Then education is simulated for members of group 2 by using their values for age and mother's level of schooling in the education equation for group 1.

The second step, for women only, is to estimate the number of children for group 1 as a function of age, mother's level of schooling (when available), region, and education. Then number of children is simulated for members of group 2 by using their values for age, mother's

[14] See Bourguignon, Ferreira, and Lustig (1998) for more exact details on how this methodology works.
[15] For the Brazilian data, where mother's level of schooling was available, we also carried out our process with an additional prior step, namely simulating mother's level of schooling. The results from this simulation are not substantially different from those reported below in the text for Brazil; the main difference is that even less of overall variance can be attributed to between-group variance once this additional leveling step is taken.

level of schooling, and (simulated) education in the fertility equation for group 1. For men, the true number of children in the household is used throughout.

The third step is to estimate the occupational sector for group 1 as a function of age, mother's level of schooling (when available), education, household composition, and number of children. Then occupational sector is simulated for members of group 2 by using their values for age, mother's level of schooling, household composition, (simulated) education, and (for women, simulated) number of children in the household in the occupational choice equation for group 1.

The final step is to estimate earnings for group 1 as a function of age, education, occupational sector, and region. Then earnings are simulated for members of group 2 by using their values for age, (simulated) education, and (simulated) occupational sector in the earnings equation for group 1.

Steps one through three utilize multinomial logit as the estimation technique as people fall into distinct groups, while step four utilizes OLS as the estimation technique for the continuous log earnings distribution. For steps one through three, we draw a randomly-generated error term for each group 2 person from a censored double exponential distribution standardized to reflect group 2's estimated error term variance. At step four, we keep the original error term for each group 2 person, but adjust it by multiplying it by the ratio of group 1's variance to group 2's variance. [16]

The simulations have real impacts on the *Z* matrices. An example of the effect that these simulations can have is shown in Table 3 for the specific case of estimating number of children for Afro-Brazilian women under the assumption that they have the same "process" for the determination of quantity of children as do white Brazilian women. While in many cases (between 66 and 82 percent of cases, conditional on the actual number of children) the same number is predicted as is actually experienced by the particular woman, in a number of other cases the procedure predicts more or fewer children (again conditional on the actual number of children and therefore upper or lower bounded for some women).

These simulations are then used to create earnings distributions for the three groups of white women, nonwhite men, and nonwhite women—while actual earnings are used for white men. The simulated wages are used to recalculate the inequality measures in Table 1.

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[16] For persons with no earnings originally, their earnings are estimated given the estimating equation and an error term is drawn for them from a normal distribution with the variance estimated from the data for that country's subgroup and then scaled up or down as described in this text sentence.

We expect that awarding the returns that white men face to the other groups and simulating the characteristics of the other groups to be more similar to those of white men would lead to within-group inequality that is more similar to that of white men, but that this process is not necessarily inequality-reducing. In Table 1, white men had the *most* unequal income in Brazil, and they were only behind nonwhite women in terms of inequality levels in Guatemala. However, we also expect that this procedure will tend to reduce between-group inequality substantially as, based on the Oaxaca-Blinder results, it is expected to have the effect of moving the simulated group 2 mean closer to the actual group 1 mean. Indeed, the simulations tend to reduce between-group inequalities, which has the potential to counteract an increase in within-group inequality in Brazil and Guatemala, for example. Thus the net effect of the simulation procedure on overall inequality measures may be increasing or decreasing in cases where group 1 has both a higher variance (or other measure of spread) and a higher mean than group 2, and it becomes an empirical question to see which effect predominates.

Results for individual earnings inequality measures

Figures 1 and 2 provide visualizations of what both the original log earnings and the simulated earnings distributions look like for a couple of cases, contrasting the full simulation results (both simulating group 2 characteristics and holding returns to characteristics constant at the group 1 level across the two groups). Figure 1 shows a case of within-gender comparison between racial groups (men in Guatemala), and Figure 2 shows a case of within-race comparison between genders (East Indians in Guyana). In both cases we see that the simulation procedure has a real impact on the earnings distributions, as the distribution peaks indeed come closer together, in the case of East Indians, generating almost overlapping distributions in spread though the peak is lower for women than for men. What is harder to tell from looking at the figures is whether or not the spread of the simulated distribution for group 2 is less than the spread of either the original distribution for group 2 or the spread of group 1's distribution. Thus we turn to our inequality measures as a way of summarizing spread.

Table 4 shows the results from these simulations in terms of how they affect earnings inequality measures (as shown in the first column of Table 1). We repeat the actual overall inequality measures for our samples in the first column, along with the results from two sets of simulations in the next six columns. The first set of simulations holds returns to characteristics constant across the two groups (at the level of the better-off group) but allows characteristics to vary. The second set of simulations not only hold returns to characteristics constant across the two groups, but also simulates characteristics using the technique outlined above. The first simulation in each set considers what would happen to the overall earnings distribution if white and non-white groups are treated the same within gender, while the second simulation considers what would happen if women are treated like men within each racial/ethnic group. The third simulation considers what would happen if both women and nonwhites are treated like white men.

All three simulations within each set are very similar to the original calculations using the observed data, with some variations depending on the inequality measure used. The Gini shows very small changes, while the Theil indices exhibit similarly very little change. There are more noticeable changes in the 90/10 and 50/10 ratios, with reductions in these ratios relative to the base case in Bolivia, Guatemala, and Guyana, and increases in the Brazilian case. However, in general, simulating equality of both returns to characteristics and characteristics distributions tends to lead to slightly higher inequality measures (closer to the original unsimulated level) than if only equality of returns to characteristics is imposed. This is a striking result that again may appear counterintuitive to those who had not seen the data in Table 1 before. In addition, significant spread remains in all four countries' earnings distributions under any of these scenarios (though less so in Guyana, which had much less spread to begin with).

Starting with the comparison of the original (column a) and the fully simulated wages (column g), there is little difference in the Ginis, but the Theil and percentile ratios show some changes. In Bolivia, inequality falls somewhat, which is likely due to the lowest inequality in that country being among white men's wages. However, white men also had the lowest inequality in Guyana, but the simulation did not yield lower Ginis in that case.

Equal treatment by race had some effect on the inequality measures. Column (e) allows differences by gender to persist, but considers the case in which nonwhite men have characteristics and skills that are comparable to white men's and similarly between nonwhite women and white women. The inequality values decrease or stay constant in Bolivia, Brazil, and Guatemala, but increase in Guyana. This may be due to the much higher inequality among Indo-Guyanese women as compared to Afro-Guyanese women, thus increasing the Afro-Guyanese women's inequality when they are given returns and characteristics that are more similar to Indo-Guyanese women.

Equal treatment by gender has no effect on the inequality measurements, except for a slight increase in Brazil (comparing columns f and a). In Brazil and Bolivia, the simulations should have created a clear increase in inequality in Brazil (since men's wages are more unequal than women's wages, regardless of race) and a decrease in Bolivia (since men's wages are more equal than women's). While the Brazilian simulations do show small changes in the expected direction, the Bolivian numbers do not show any notable changes.

Within- versus between-group inequality for individual earnings measures

The change in overall inequality, as shown in Table 4, tells us something about the within-group inequality, but tells us nothing about the extent of wage inequality between groups—which is the usual concern in group wage differentials—and it does not tell us whether within-group or between-group inequality is the main culprit in causing high overall inequality. To examine these two questions, we decompose the Theil (1) index into within and between sections, thereby showing very simply how much of inequality occurs within defined groups rather than between one or more defined groups.[17] Such a decomposition is shown in Table 5 for both the actual and the simulated inequality measures, where the simulations are again done with either allowing only the betas to be simulated, or both the betas and the characteristics to be simulated. We perform both an overall decomposition and decompositions for various population subgroups, including white and nonwhite men, white and nonwhite women, white men and women, nonwhite men and women, and white men and nonwhite women.

For all such decompositions, it is clear that the majority of inequality occurs within rather than between the population subgroups, reinforcing the patterns found in Table 4. While there tends to be more of a "between" effect in comparing racial/ethnic subgroups than in comparing genders (except for Guyana, where there is little between effect in either set of comparisons), the between effect is still dominated by the "within" effect. In addition, there is little difference in the decompositions between the actual and simulated earnings comparisons, implying little effect

[17] We performed these decompositions for the Theil (0) index as well; the results are virtually identical in terms of the percentage attributable to between vs. within effects and thus we do not present those results; they are available the technical appendix in expanded Tables 5 and 7.

on overall earnings inequality of equalizing pay structures across groups in comparison to almost any equalization that might occur within groups.

The virtual absence of effects on the inequality measures of treating everyone like men may be due to several factors other than the argument that we are implicitly advancing, namely that overall inequality is significant within groups and dwarfs the significance of factors creating between-group inequality. First, the goodness of fit of some of the simulation equations was low, so the extent to which the simulations were able to proxy the white men's distribution of particular variables is limited. Second, and related to the first point, the variables that are used to simulate the new distribution of explanatory variables are themselves based on processes of being from a racial, ethnic, or gender group, so the simulations may be picking up the influences of some group-specific characteristics that the method is intended to purge. Third, the regressions omit many variables (due to data unavailability) that may be key to simulating the distribution of endowments or estimating the rewarding of endowments. Most notably, the methodology cannot capture the quality or importance of institutions that drive the observed differentials, cannot control for differences in preferences, and does not control well for some variables such as actual labor market experience (generally considered to be a key determinant of gender wage differentials) or spatial dimensions of inequality that may be key to the ethnic and racial wage differentials. Nonetheless, these results are striking in their consistency and size across both country and simulation technique.

Results for per capita household earnings inequality measures

All of the results up to this point in the paper have been in comparing individual earnings rather than either a broader measure of individual income or a broader measure of earnings or income potentially available to the individual, such as household total earnings or income. While these data sets do not yield good measures of income for us to use (and indeed, our focus in this paper is on labor income rather than overall income inequality), we can calculate household earnings measures to see how our various simulations affect household earnings. Rather than also simulating different household structures, we standardize our comparisons to a per capita household earnings basis in the following two tables. However, this does allow us to see how per capita household earnings inequality among say, white men, is affected by the potentially higher (or lower) earnings that their spouses might earn under our various simulations. In other words, we can compare available pooled labor earnings for members of our various gender and racial/ethnic groups rather than simply their individual earnings. This involves simulating earnings for individuals in the sample, aggregating them into their actual households, and then ascribing per capita earnings to each individual by dividing by the number of people in their household (including nonearning dependents).

Table 6 shows measures comparable to Table 4 calculated for the per capita household earnings measure. Household per capita earnings inequality measures are uniformly higher than the comparable individual earnings inequality measures (though not as markedly so in Guyana as in the other three countries). And the indexes show more significant relative reductions under the various simulations than do individual returns (though generally not falling to a level below the individual return simulation levels). Again, simulation of both returns and characteristics (columns e through g) leads to less decrease in inequality than simulation of returns alone (columns b through d).

Table 7 shows Theil (1) index decompositions comparable to the first panel of Table 5 using the per capita household earnings measure, namely for the case in which we observe how overall per capita household earnings inequality for the society is affected if everyone is treated like white men. Here again one notices the more substantial drop in inequality caused by equalizing treatment of persons and then pooling them into household earnings pools. However, the contribution of between-group inequality to overall inequality remains low (never over fourteen percent of the total) and drops when either form of simulation is run, again as in the case of individual earnings as shown in Table 5.

Hence the results based on individual earnings inequality can be qualified somewhat to say that moves to equalize returns and characteristics distributions between gender-racial-ethnic groups will reduce household per capita earnings inequality measurably, but substantial inequality remains (particularly given the higher level of inequality measured on the household rather than the individual level), and the remaining inequality is still (not surprisingly) predominantly within-group rather than between-group inequality.

Conclusions and Implications for Policy

In this paper we have shown that within-group, rather than between-group, inequality is the key factor underlying the high inequality observed in these four Latin American countries.

While between-group differentials have been a primary focus of academics interested in considering inequality and its causes, reduction of such differentials is not likely to be the key to diminishing overall inequality, at least in the Latin American context.

We have also shown in this paper that decreasing within-group inequality is quite difficult, as making adjustments at obvious entry points for such steps has little effect on the overall wage distribution. When we simulated rewarding women the same as men, indigenous the same as non-indigenous, or black the same as white—any or all of which might occur in affirmative action programs—overall measured inequality changed little.[18] Similarly, when we simulated equalizing endowment accumulation processes among groups, there was again little change in the overall inequality measures.

These results underscore the extent to which overall inequality in Latin America need not be particularly linked with treatment or endowment differences between groups. From a policy point of view this point has three implications. First, poverty reduction and/or income equalization policies do not automatically need to target race or ethnic groups to be effective.[19] Instead, they can be targeted based on earnings standards alone—since there are poor across all racial and ethnic groups. Second, anti-discrimination policies, even if successful, will not automatically lead to lower earnings inequality.[20] It is particularly important to untwine anti-discrimination policies from inequality reduction policies rather than assuming that the former will serve as the latter as well. Third, policies that attempt to equalize earnings-related characteristics across the whole population, say guaranteeing universal primary and hopefully also secondary education, may do more to equalize earnings than enforcement of standard anti-discrimination policies. The World Bank (World Bank 2004, Chapter 7) and other international and national policymaker groups have proposed a wide range of possibilities for changing the educational system (vouchers, conditional cash transfers, decentralization, etc.). These need further evaluation in light of thinking about whether they will replicate inequality or reduce it.

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[18] Curiously, there are few economic studies of affirmative action in the Latin American context (World Bank 2004). Andrade (2004) considers the effects of quotas in universities in Brazil; Htun (2004, 2000) discusses affirmative action in Brazil and gender quotas in LAC more generally.

[19] We have purposely not discussed the relationship between poverty and inequality in this paper so as not to confound the two concepts. Several recent works discuss poverty rates and patterns in the LAC context, including Wodon (2000), Wodon et al. (2001), and Gasparini et al. (2007). Notably, Gasparini et al. find heterogeneous patterns for the LAC region in terms of poverty changes and economic growth.

[20] This point is made in Jacobsen (2004), which considers the US case and the rising inequality among women over the past few decades; in simulations similar to those in this paper, treating women more like men makes inequality

Indeed, the microsimulation technique utilized in this paper can be of use in predicting the effects of various policies, both those that are explicitly redistributional and those that have redistributional side effects, whether intended or unintended.[21] In addition, by allowing for simulation of characteristics, such as educational attainment and fertility, that are pre-labor market (or outside of the labor market), policies that do not affect labor market institutions directly may be simulated to see what their effects are on earnings. Such simulations may provide a useful supplement, a pre-test, or an alternative to vastly more expensive and time-consuming random treatment experiments in the field.[22]

One extension of the work we do herein would be to consider programs that alter household structure, again either purposefully or inadvertently. In our simulations, we take household structure as fixed rather than allowing for changes in household structure to occur as a reaction to changes in either characteristics or returns to characteristics. Thus in our per capita household earnings measures, no change was hypothesized to occur in household composition that would affect these measures. This extension would require additional assumptions and steps in the simulation procedure, but would allow for discussion and prediction of these effects.

Reform suggestions that operate directly on the labor market can be modeled as well to see what effect they will have on the earnings distribution and thus on earnings and income inequality. Again, assumptions would have to be made about how occupational sector distributions and/or returns to characteristics are affected, but then hot-button topics like the effects of minimum wages or of labor market liberalization on earnings distributions and inequality measures could be modeled. For instance, much of the research so far on the effects of minimum wages in Latin American countries appears to indicate it has negative effects, but most of the research has not utilized measures of earnings inequality.[23] Similarly, the effects of

rise more, particularly in the earlier decades when labor market discrimination was likely much stronger (i.e., before women's wages began rising notably relative to men in the mid 1980s).

[21] See Bourguignon and Spadaro (2006) for additional discussion of the use of microsimulation as a tool for evaluating redistribution policies.

[22] Indeed, in the Latin American context at least, there are relatively few such evaluation studies that consider differences; Patrinos et al. (2005) actually evaluate the impact of the Progresa program in Mexico on different ethnicities, and Schady and Araujo (2006) consider ethnic differences in program effects in the Ecuadorean context.

[23] There is certainly debate regarding minimum wage effects in Latin America. Maloney and Nunez (2000) conclude the effects are large and relatively negative for their sample of 8 countries, and Arango and Pachon (2004) find negative employment effects particularly on the poor and on women in Colombia. Cunningham and Kristensen (2000), for a sample of 19 Latin American and Caribbean counties, and Neumark et al. (2006) focus on different effects on different parts of the wage distribution, but do not find clear benefits for low-wage workers. On the other hand, Fairris et al. (2006) conclude that declining real value of the minimum wage in Mexico, combined with other changes in the Mexican wage structure, was a source for the increase in wage inequality in the 80s and 90s.

labor market liberalization—or the potential flip side of increased or maintained protection—on inequality are disputed. On the one hand, some commentators (Arias et al. 2005, Cunningham and Santamaria 2003, Heller and Mahoney 2003) argue that the current set of labor regulations does not serve workers or firms well and also have negative effects through maintaining or increasing the size of the informal sector. On the other hand, liberalization does not appear to have a positive effect on inequality either—one World Bank report concludes that liberalization in Latin America and the Caribbean has led to "on balance mild disequalizing effects" (World Bank 2004, p. 221). One possibility is that liberalization may lead to income growth but not lower inequality, as de Janvry and Sadoulet (2000) find for 12 Latin American countries between 1970 and 1994 (where they find reductions in poverty but not in inequality). Microsimulations may help us elucidate where there are countervailing factors as well as which factor tends to prevail to cause a net change in inequality.

A more difficult challenge for the microsimulation methodology, at least given current data constraints, is how to add in factors like differential access to social networks to gauge their effects on economic inequality. It is likely that social networks, and the different results they can generate by gender and racial/ethnic group, are a key factor in generating inequality.[24] To the extent that processes such as these are not included in formal modeling, then the modeling results will always be open to criticism for not being able to model fully the complex dynamics that generate inequality. This will be an important task for future researchers.

Our conclusions may be viewed as radical by those who have considered inequality in Latin America to have a large racial and/or ethnic dimension. Clearly other dimensions of inequality need to be considered besides earnings inequality, and shortcomings of the available data that we use need to be considered as well in terms of their ability to capture the full range of economic outcomes that people experience. Nevertheless, our results, based on large survey data, relatively consistent across four countries, and utilizing a range of calculations in order to provide some robustness check, set up a challenge for those who would draw inferences based on alternative data that may be actually less rather than more representative of the actual situation in Latin America. We hope that others will follow our path of considering how to develop quantitative measurements of the extent and nature of inequality along this and other dimensions

[24] Se Lunde et al. (2007), which looks at social networks in five countries and their role in generating income for indigenous peoples.

in order that both measurement and policy may proceed conditioned on ever-increasing and more reliable information about how inequality operates within societies.

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Table 1: Earnings inequality measures; overall and by gender-racial/ethnic group

	All	White men	Nonwhite men	White women	Nonwhite women
Theil(1)					
Bolivia	0.60	0.47	0.53	0.56	0.69
Brazil	0.65	0.60	0.51	0.59	0.50
Guatemala	0.78	0.73	0.55	0.67	0.69
Guyana	0.32	0.32	0.29	0.41	0.26
Theil(0)					
Bolivia	0.73	0.52	0.69	0.61	0.82
Brazil	0.58	0.56	0.45	0.53	0.44
Guatemala	0.86	0.72	0.65	0.85	0.85
Guyana	0.29	0.27	0.27	0.34	0.26
Gini					
Bolivia	0.56	0.51	0.53	0.54	0.60
Brazil	0.57	0.56	0.51	0.54	0.49
Guatemala	0.61	0.59	0.54	0.58	0.61
Guyana	0.39	0.37	0.39	0.43	0.37
90th percentile /10th percentile wages					
Bolivia	35.4	14.5	32.6	20.4	39.0
Brazil	10.4	13.7	8.8	10.0	9.0
Guatemala	36.8	23.2	26.2	43.2	42.8
Guyana	5.5	4.3	5.1	4.9	5.2
50th percentile /10th percentile wages					
Bolivia	9.8	4.2	10.7	5.9	9.6
Brazil	2.6	3.4	2.5	2.5	2.8
Guatemala	10.3	6.3	7.5	12.8	8.0
Guyana	2.6	2.3	2.0	2.4	2.6

Table 2: Log earnings decompositions

	Differential	Attributed to differences in characteristics	Attributed to differences in coefficients
Decompositions of white men/women wage differentials			
Bolivia	0.29	-0.07 (-24%)	0.36 (124%)
Brazil	0.41	-0.12 (-29%)	0.53 (129%)
Guatemala	0.92	0.14 (15%)	0.78 (85%)
Guyana	0.56	0.01 (2%)	0.55 (98%)
Decompositions of nonwhite men/women wage differentials			
Bolivia	0.39	-0.05 (-13%)	0.44 (113%)
Brazil	0.38	-0.14 (-37%)	0.52 (137%)
Guatemala	0.80	0.23 (29%)	0.57 (71%)
Guyana	0.63	-0.07 (-111%)	0.70 (111%)
Decompositions of white/nonwhite men wage differentials			
Bolivia	0.94	0.57 (61%)	0.37 (39%)
Brazil	0.62	0.47 (76%)	0.15 (24%)
Guatemala	0.72	0.44 (61%)	0.28 (39%)
Guyana	0.01	-0.04 (-400%)	0.05 (500%)
Decompositions of white/nonwhite women wage differentials			
Bolivia	1.04	0.65 (63%)	0.39 (37%)
Brazil	0.58	0.46 (79%)	0.12 (21%)
Guatemala	0.60	0.45 (75%)	0.15 (25%)
Guyana	0.07	-0.13 (-186%)	0.20 (-286%)
Decompositions of white men/nonwhite women wage differentials			
Bolivia	1.33	0.51 (38%)	0.82 (62%)
Brazil	1.00	0.31 (31%)	0.69 (69%)
Guatemala	1.52	0.65 (43%)	0.87 (57%)
Guyana	0.63	-0.11 (-17%)	0.74 (117%)

Table 3: Simulated v. actual number of children, women, Brazil

		Simulated number of children in actual terms						
		0	1	2	3	4	>4	Total
Actual number of children	0	2974068	62837	45063	8299	3915	549472	3643654
	1	166252	2841511	20134	529	213	496346	3524985
	2	156287	64255	2710228	0	1212	442859	3374841
	3	105332	96573	80433	1504710	6945	275641	2069634
	4	56890	55098	69251	15938	662625	136922	996724
	>4	53675	71626	105656	32697	13047	660480	937181
Total		3512504	3191900	3030765	1562173	687957	2561720	14547019

		Simulated number of children in percentage terms					
		0	1	2	3	4	>4
Actual number of children	0	0.8162	0.0172	0.0124	0.0023	0.0011	0.1508
	1	0.0472	0.8061	0.0057	0.0002	0.0001	0.1408
	2	0.0463	0.0190	0.8031	0.0000	0.0004	0.1312
	3	0.0509	0.0467	0.0389	0.7270	0.0034	0.1332
	4	0.0571	0.0553	0.0695	0.0160	0.6648	0.1374
	>4	0.0573	0.0764	0.1127	0.0349	0.0139	0.7048

Figure 1: Simulated v. actual log earnings distributions, Men, Guatemala

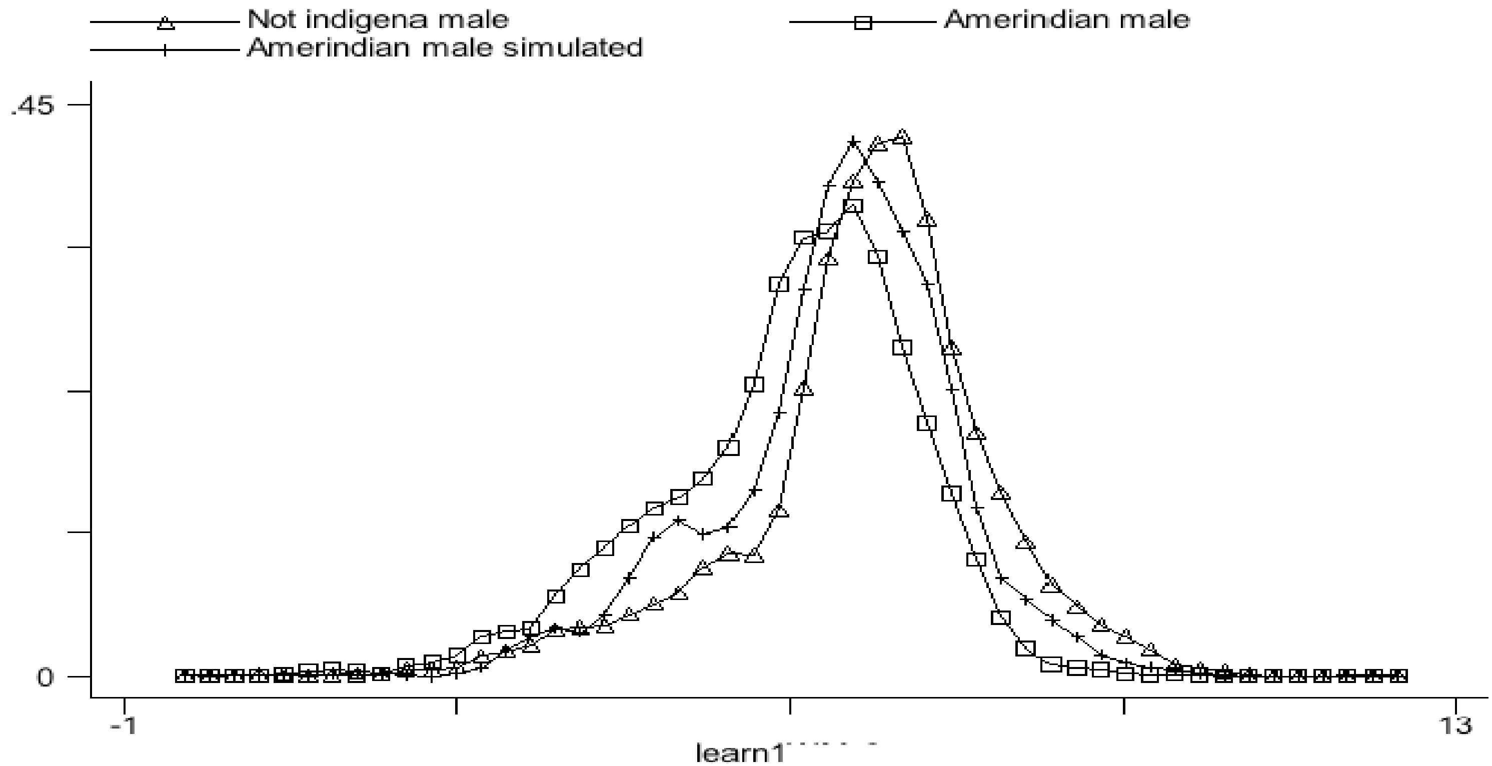

Figure 2: Simulated v. actual log earnings distributions, East Indians, Guyana

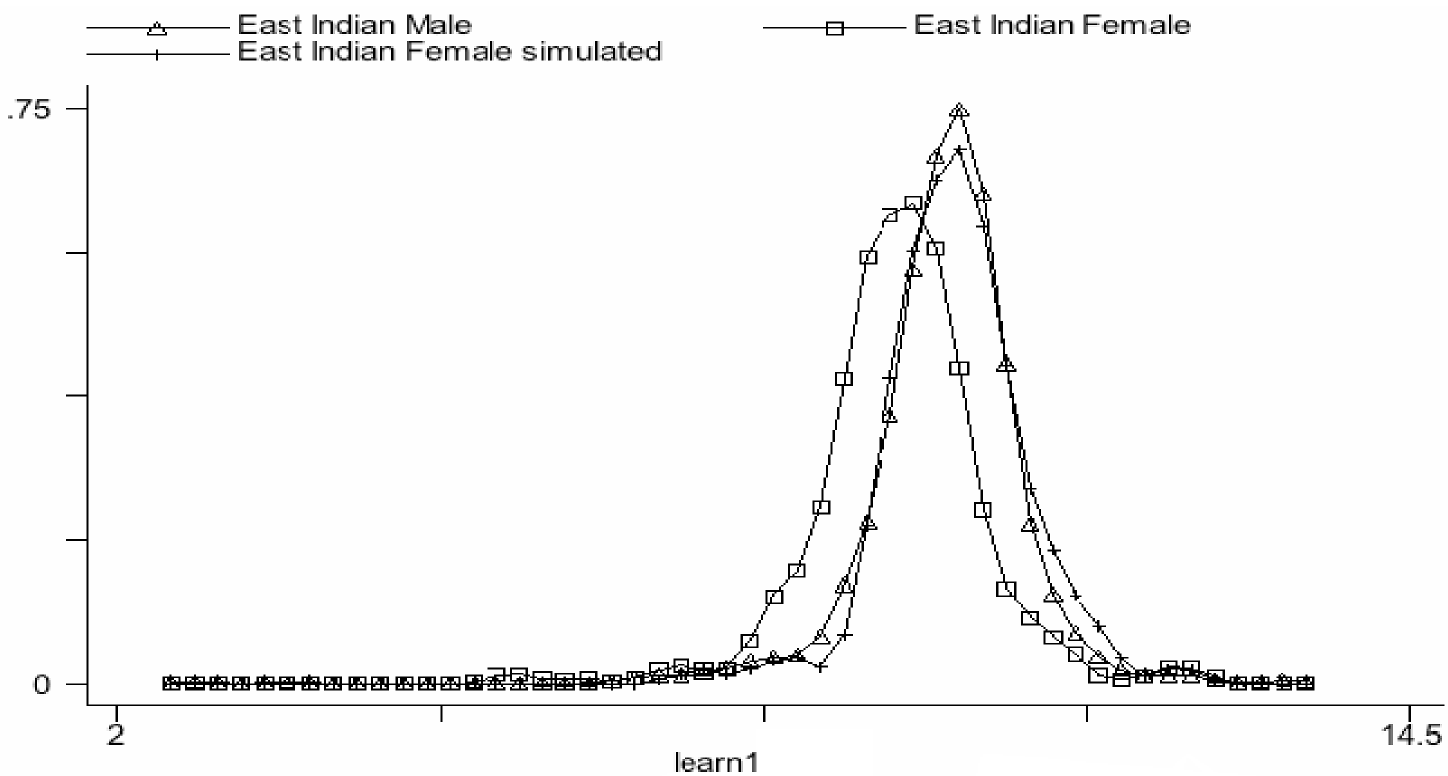

Table 4: Inequality measures for earnings, based on actual and simulated earnings within racial/ethnic group and within gender

		Simulating returns only			Simulating returns and characteristics		
	Observed	equal treatment by race/ethnicity within gender	Equal treatment by gender within race/ethnicity	all segments treated as white men	equal treatment by race/ethnicity within gender	equal treatment by gender within race/ethnicity	all segments treated as white men
	(a)	(b)	(c)	(d)	(e)	(f)	(g)
Theil(1)							
Bolivia	0.60	0.53	0.56	0.51	0.57	0.58	0.55
Brazil	0.65	0.61	0.64	0.63	0.64	0.66	0.65
Guatemala	0.78	0.75	0.79	0.76	0.75	0.76	0.79
Guyana	0.32	0.35	0.32	0.34	0.36	0.31	0.33
Theil(0)							
Bolivia	0.73	0.63	0.68	0.59	0.66	0.72	0.65
Brazil	0.58	0.57	0.58	0.57	0.58	0.59	0.59
Guatemala	0.86	0.85	0.89	0.84	0.81	0.77	0.86
Guyana	0.29	0.31	0.27	0.29	0.31	0.28	0.30
Gini							
Bolivia	0.56	0.54	0.55	0.53	0.55	0.56	0.55
Brazil	0.57	0.56	0.57	0.56	0.56	0.59	0.57
Guatemala	0.61	0.61	0.62	0.61	0.59	0.60	0.63
Guyana	0.39	0.41	0.38	0.40	0.40	0.39	0.40
90th percentile wages /10th percentile wages							
Bolivia	35.4	24.3	31.3	22.2	26.9	34.0	26.6
Brazil	10.4	11.8	12.2	12.1	14.2	15.5	16.7
Guatemala	36.8	32.5	27.2	23.9	30.3	28.3	21.4
Guyana	5.5	5.4	4.7	4.9	5.3	4.7	4.7
50th percentile wages /10th percentile wages							
Bolivia	9.8	7.5	9.7	7.1	7.6	9.9	7.7
Brazil	2.6	2.9	2.9	2.9	3.5	3.3	4.2
Guatemala	10.3	9.3	7.9	7.2	8.7	7.5	5.8
Guyana	2.6	2.4	2.2	2.3	2.5	2.2	2.3

Table 5: Theil(1) index decompositions, individual earnings inequality

	Overall earnings inequality			Among men by race/ethinicity			Among women by race/ethinicity			Among whites by gender			Among nonwhites by gender			Among white men and nonwhite women		
	Total	**Within**	**Between**	**Total**	**Within**	**Between**	**Total**	**Within**	**Between**	**Total**	**Within**	**Between**	**Total**	**Within**	**Between**	**Total**	**Within**	**Between**
Bolivia																		
Observed earnings	0.60	0.53	0.07 (12%)	0.55	0.50	0.05 (9%)	0.68	0.61	0.07 (10%)	0.51	0.50	0.01 (2%)	0.59	0.57	0.02 (3%)	0.63	0.52	0.12 (18%)
Simulated earnings - returns only	0.51	0.48	0.03 (6%)	0.49	0.47	0.03 (5%)	0.59	0.56	0.04 (6%)	0.50	0.50	0.00 (0%)	0.54	0.53	0.00 (1%)	0.49	0.47	0.02 (6%)
Simulated earnings - returns & characteristics	0.55	0.54	0.01 (2%)	0.54	0.53	0.01 (2%)	0.62	0.61	0.00 (1%)	0.47	0.47	0.00 (0%)	0.62	0.62	0.01 (1%)	0.52	0.51	0.01 (2%)
Brazil																		
Observed earnings	0.65	0.57	0.07 (11%)	0.63	0.57	0.06 (10%)	0.61	0.57	0.05 (7%)	0.62	0.60	0.02 (3%)	0.52	0.51	0.01 (2%)	0.67	0.59	0.08 (12%)
Simulated earnings - returns only	0.63	0.60	0.03 (5%)	0.62	0.59	0.04 (5%)	0.60	0.57	0.03 (5%)	0.61	0.61	0.00 (0%)	0.52	0.52	0.00 (0%)	0.62	0.60	0.02 (3%)
Simulated earnings - returns & characteristics	0.65	0.63	0.02 (3%)	0.63	0.61	0.02 (3%)	0.60	0.58	0.02 (3%)	0.62	0.62	0.00 (0%)	0.51	0.51	0.00 (0%)	0.62	0.61	0.01 (2%)
Guatemala																		
Observed earnings	0.78	0.69	0.09 (12%)	0.76	0.69	0.07 (9%)	0.76	0.68	0.08 (11%)	0.74	0.72	0.02 (3%)	0.61	0.58	0.03 (5%)	0.83	0.73	0.10 (12%)
Simulated earnings - returns only	0.71	0.67	0.04 (6%)	0.79	0.70	0.09 (11%)	0.74	0.68	0.06 (8%)	0.74	0.72	0.02 (3%)	0.55	0.55	0.00 (0%)	0.74	0.73	0.01 (1%)
Simulated earnings - returns & characteristics	0.75	0.75	0.01 (1%)	0.75	0.74	0.01 (1%)	0.69	0.69	0.00 (0%)	0.72	0.72	0.00 (0%)	0.57	0.57	0.00 (0%)	0.74	0.76	0.00 (0%)
Guyana																		
Observed earnings	0.33	0.31	0.02 (6%)	0.31	0.31	0.00 (0%)	0.31	0.31	0.00 (0%)	0.35	0.34	0.01 (3%)	0.30	0.28	0.02 (7%)	0.32	0.30	0.02 (6%)
Simulated earnings - returns only	0.34	0.34	0.00 (0%)	0.33	0.33	0.00 (0%)	0.37	0.36	0.01 (3%)	0.33	0.33	0.00 (0%)	0.30	0.29	0.00 (1%)	0.33	0.33	0.00 (0%)
Simulated earnings - returns & characteristics	0.33	0.33	0.00 (0%)	0.34	0.34	0.00 (0%)	0.41	0.41	0.00 (0%)	0.34	0.34	0.00 (0%)	0.30	0.30	0.00 (0%)	0.32	0.32	0.00 (0%)

Table 6: Inequality measures for per capita household earnings, based on actual and simulated earnings within racial/ethnic group and within gender

		Simulating returns only			Simulating returns and characteristics		
	Observed	equal treatment by race/ethnicity within gender	Equal treatment by gender within race/ethnicity	all segments treated as white men	equal treatment by race/ethnicity within gender	equal treatment by gender within race/ethnicity	all segments treated as white men
	(a)	(b)	(c)	(d)	(e)	(f)	(g)
Theil(1)							
Bolivia	0.77	0.55	0.57	0.50	0.59	0.63	0.57
Brazil	0.72	0.65	0.73	0.67	0.66	0.72	0.66
Guatemala	0.87	0.76	0.82	0.79	0.75	0.79	0.76
Guyana	0.37	0.33	0.31	0.33	0.32	0.31	0.32
Theil(0)							
Bolivia	0.93	0.67	0.75	0.60	0.78	0.82	0.71
Brazil	0.68	0.63	0.69	0.65	0.63	0.68	0.64
Guatemala	0.97	0.86	0.92	0.86	0.85	0.89	0.84
Guyana	0.35	0.30	0.28	0.31	0.31	0.28	0.30
Gini							
Bolivia	0.62	0.55	0.56	0.53	0.57	0.58	0.56
Brazil	0.60	0.58	0.60	0.58	0.58	0.60	0.58
Guatemala	0.65	0.61	0.63	0.63	0.61	0.62	0.61
Guyana	0.44	0.40	0.39	0.40	0.41	0.39	0.40
90th percentile wages /10th percentile wages							
Bolivia	62.0	29.0	43.6	23.6	44.6	49.4	37.6
Brazil	17.9	16.4	19.1	17.6	16.8	18.1	17.1
Guatemala	49.5	33.9	42.8	34.5	37.0	40.9	35.5
Guyana	6.9	5.3	5.2	5.7	5.6	5.2	5.2
50th percentile wages /10th percentile wages							
Bolivia	14.5	7.7	11.7	6.3	11.4	12.2	10.1
Brazil	4.0	3.8	4.2	4.0	3.9	4.1	4.0
Guatemala	10.5	8.1	9.8	8.0	9.5	10.1	9.0
Guyana	2.6	2.5	2.3	2.5	2.4	2.4	2.3

Table 7: Theil(1) index decompositions, per capita household earnings inequality

	Total	White Men	Nonwhite Men	White Women	Nonwhite Women	Within	Between
Bolivia							
Observed earnings	0.77	0.69	0.63	0.65	0.76	0.66	0.11 (14%)
Simulated earnings - returns only	0.57	0.47	0.50	0.67	0.40	0.50	0.07 (12%)
Simulated earnings - returns & characteristics	0.50	0.45	0.55	0.39	0.53	0.49	0.01 (2%)
Brazil							
Observed earnings	0.72	0.66	0.58	0.65	0.57	0.64	0.08 (11%)
Simulated earnings - returns only	0.72	0.67	0.62	0.67	0.62	0.66	0.06 (8%)
Simulated earnings - returns & characteristics	0.85	0.74	0.92	0.82	0.96	0.84	0.01 (1%)
Guatemala							
Observed earnings	0.87	0.83	0.62	0.55	0.75	0.77	0.10 (11%)
Simulated earnings - returns only	0.76	0.74	0.55	0.50	0.59	0.68	0.08 (11%)
Simulated earnings - returns & characteristics	0.79	0.74	0.92	0.82	0.75	0.77	0.02 (2%)
Guyana							
Observed earnings	0.37	0.33	0.42	0.31	0.30	0.36	0.01 (3%)
Simulated earnings - returns only	0.32	0.31	0.35	0.23	0.34	0.32	0.00 (0%)
Simulated earnings - returns & characteristics	0.33	0.31	0.36	0.20	0.51	0.32	0.01 (2%)

Table 5: Theil index of earnings inequality decompositions

(i) Decomposition of overall earnings inequality

	Total	White Men	Nonwhite Men	White Women	Nonwhite Women	Within	Between
Bolivia							
Observed earnings							
Theil (1)	0.60	0.47	0.53	0.56	0.69	0.53	0.07 (12%)
Theil (0)	0.73	0.52	0.69	0.61	0.82	0.66	0.07 (10%)
Simulated earnings — returns only							
Theil (1)	0.51	0.47	0.47	0.54	0.49	0.48	0.03 (6%)
Theil (0)	0.59	0.52	0.58	0.56	0.64	0.56	0.03 (5%)
Simulated earnings — returns and characteristics							
Theil (1)	0.55	0.47	0.63	0.44	0.62	0.54	0.01 (2%)
Theil (0)	0.65	0.52	0.74	0.55	0.74	0.64	0.01 (2%)
Brazil							
Observed earnings							
Theil (1)	0.65	0.60	0.51	0.59	0.50	0.57	0.07 (11%)
Theil (0)	0.58	0.56	0.45	0.53	0.44	0.50	0.08 (14%)
Simulated earnings — returns only							
Theil (1)	0.63	0.60	0.56	0.62	0.59	0.60	0.03 (5%)
Theil (0)	0.57	0.56	0.50	0.57	0.52	0.54	0.04 (7%)
Simulated earnings — returns and characteristics							
Theil (1)	0.65	0.60	0.63	0.66	0.66	0.63	0.02 (3%)
Theil (0)	0.59	0.56	0.54	0.59	0.57	0.56	0.02 (4%)
Guatemala							
Observed earnings							
Theil (1)	0.78	0.73	0.55	0.67	0.69	0.69	0.09 (12%)
Theil (0)	0.86	0.72	0.65	0.85	0.85	0.75	0.11 (13%)
Simulated earnings — returns only							
Theil (1)	0.71	0.73	0.51	0.63	0.44	0.67	0.04 (6%)
Theil (0)	0.71	0.72	0.58	0.66	0.63	0.67	0.05 (6%)
Simulated earnings — returns and characteristics							
Theil (1)	0.75	0.73	0.86	0.68	1.29	0.75	0.01 (1%)
Theil (0)	0.74	0.72	0.81	0.67	0.93	0.73	0.01 (1%)
Guyana							
Observed earnings							
Theil (1)	0.33	0.32	0.29	0.41	0.26	0.31	0.02 (6%)
Theil (0)	0.29	0.27	0.27	0.34	0.26	0.28	0.02 (5%)
Simulated earnings — returns only							
Theil (1)	0.34	0.32	0.34	0.36	0.41	0.34	0.00 (0%)
Theil (0)	0.29	0.27	0.30	0.29	0.43	0.29	0.00 (0%)
Simulated earnings — returns and characteristics							
Theil (1)	0.33	0.32	0.39	0.27	0.35	0.33	0.00 (0%)
Theil (0)	0.29	0.27	0.35	0.22	0.37	0.29	0.00 (0%)

Table 5 (continued)

(ii) Decomposition of earnings inequality among men by race/ethnicity

	Total	White Men	Nonwhite Men	Within	Between
Bolivia					
Observed earnings					
Theil (1)	0.55	0.47	0.53	0.50	0.05 (9%)
Theil (0)	0.67	0.52	0.69	0.62	0.05 (7%)
Simulated earnings — returns only					
Theil (1)	0.49	0.47	0.47	0.47	0.03 (5%)
Theil (0)	0.58	0.52	0.58	0.55	0.03 (5%)
Simulated earnings — returns and characteristics					
Theil (1)	0.54	0.47	0.63	0.53	0.01 (2%)
Theil (0)	0.63	0.52	0.74	0.62	0.01 (2%)
Brazil					
Observed earnings					
Theil (1)	0.63	0.60	0.51	0.57	0.06 (10%)
Theil (0)	0.57	0.56	0.45	0.51	0.06 (11%)
Simulated earnings — returns only					
Theil (1)	0.62	0.60	0.56	0.59	0.04 (5%)
Theil (0)	0.57	0.56	0.50	0.53	0.04 (7%)
Simulated earnings — returns and characteristics					
Theil (1)	0.63	0.60	0.63	0.61	0.02 (3%)
Theil (0)	0.57	0.56	0.54	0.55	0.02 (4%)
Guatemala					
Observed earnings					
Theil (1)	0.76	0.73	0.55	0.69	0.07 (9%)
Theil (0)	0.77	0.72	0.65	0.69	0.08 (10%)
Simulated earnings — returns only					
Theil (1)	0.79	0.74	0.55	0.70	0.09 (11%)
Theil (0)	0.86	0.82	0.67	0.76	0.10 (12%)
Simulated earnings — returns and characteristics					
Theil (1)	0.75	0.73	0.86	0.74	0.01 (1%)
Theil (0)	0.74	0.72	0.81	0.73	0.01 (1%)
Guyana					
Observed earnings					
Theil (1)	0.31	0.32	0.29	0.31	0.00 (0%)
Theil (0)	0.27	0.27	0.27	0.27	0.00 (0%)
Simulated earnings — returns only					
Theil (1)	0.33	0.32	0.34	0.33	0.00 (0%)
Theil (0)	0.29	0.27	0.30	0.29	0.00 (0%)
Simulated earnings — returns and characteristics					
Theil (1)	0.34	0.32	0.39	0.34	0.00 (0%)
Theil (0)	0.28	0.27	0.35	0.28	0.00 (0%)

Table 5 (continued)

(iii) Decomposition of earnings inequality among women by race/ethnicity

	Total	White Women	Nonwhite Women	Within	Between
Bolivia					
Observed earnings					
Theil (1)	0.68	0.56	0.69	0.61	0.07 (10%)
Theil (0)	0.80	0.61	0.82	0.73	0.07 (9%)
Simulated earnings — returns only					
Theil (1)	0.59	0.56	0.55	0.56	0.04 (6%)
Theil (0)	0.68	0.61	0.67	0.64	0.04 (6%)
Simulated earnings — returns and characteristics					
Theil (1)	0.62	0.56	0.72	0.61	0.00 (1%)
Theil (0)	0.69	0.61	0.82	0.68	0.01 (1%)
Brazil					
Observed earnings					
Theil (1)	0.61	0.59	0.50	0.57	0.05 (7%)
Theil (0)	0.55	0.53	0.44	0.49	0.05 (10%)
Simulated earnings — returns only					
Theil (1)	0.60	0.59	0.52	0.57	0.03 (5%)
Theil (0)	0.54	0.53	0.46	0.50	0.04 (7%)
Simulated earnings — returns and characteristics					
Theil (1)	0.60	0.59	0.56	0.58	0.02 (3%)
Theil (0)	0.54	0.53	0.50	0.52	0.02 (4%)
Guatemala					
Observed earnings					
Theil (1)	0.76	0.67	0.69	0.68	0.08 (11%)
Theil (0)	0.95	0.85	0.85	0.85	0.10 (11%)
Simulated earnings — returns only					
Theil (1)	0.74	0.67	0.73	0.68	0.06 (8%)
Theil (0)	0.94	0.85	0.93	0.88	0.07 (6%)
Simulated earnings — returns and characteristics					
Theil (1)	0.69	0.67	0.84	0.69	0.00 (0%)
Theil (0)	0.87	0.85	1.05	0.86	0.01 (1%)
Guyana					
Observed earnings					
Theil (1)	0.31	0.41	0.26	0.31	0.00 (0%)
Theil (0)	0.29	0.34	0.26	0.29	0.00 (0%)
Simulated earnings — returns only					
Theil (1)	0.37	0.41	0.34	0.36	0.01 (3%)
Theil (0)	0.34	0.34	0.33	0.33	0.01 (3%)
Simulated earnings — returns and characteristics					
Theil (1)	0.41	0.41	0.39	0.41	0.00 (0%)
Theil (0)	0.35	0.34	0.43	0.35	0.00 (0%)

Table 5 (continued)

(iv) Decomposition of earnings inequality among whites by gender

	Total	White Men	White Women	Within	Between
Bolivia					
Observed earnings					
Theil (1)	0.51	0.47	0.56	0.50	0.01 (2%)
Theil (0)	0.57	0.52	0.61	0.55	0.01 (3%)
Simulated earnings — returns only					
Theil (1)	0.50	0.47	0.54	0.50	0.00 (0%)
Theil (0)	0.53	0.52	0.56	0.53	0.00 (0%)
Simulated earnings — returns and characteristics					
Theil (1)	0.47	0.47	0.44	0.47	0.00 (0%)
Theil (0)	0.53	0.52	0.55	0.53	0.00 (0%)
Brazil					
Observed earnings					
Theil (1)	0.62	0.60	0.59	0.60	0.02 (3%)
Theil (0)	0.57	0.56	0.53	0.55	0.02 (4%)
Simulated earnings — returns only					
Theil (1)	0.61	0.60	0.62	0.61	0.00 (0%)
Theil (0)	0.56	0.56	0.57	0.56	0.00 (0%)
Simulated earnings — returns and characteristics					
Theil (1)	0.62	0.60	0.66	0.62	0.00 (0%)
Theil (0)	0.57	0.56	0.59	0.57	0.00 (0%)
Guatemala					
Observed earnings					
Theil (1)	0.74	0.73	0.67	0.72	0.02 (3%)
Theil (0)	0.79	0.72	0.85	0.77	0.02 (3%)
Simulated earnings — returns only					
Theil (1)	0.74	0.73	0.67	0.72	0.02 (3%)
Theil (0)	0.79	0.72	0.85	0.77	0.02 (3%)
Simulated earnings — returns and characteristics					
Theil (1)	0.72	0.73	0.68	0.72	0.00 (0%)
Theil (0)	0.71	0.72	0.67	0.71	0.00 (0%)
Guyana					
Observed earnings					
Theil (1)	0.35	0.32	0.41	0.34	0.01 (3%)
Theil (0)	0.30	0.27	0.34	0.28	0.01 (5%)
Simulated earnings — returns only					
Theil (1)	0.33	0.32	0.36	0.33	0.00 (0%)
Theil (0)	0.27	0.27	0.29	0.27	0.00 (0%)
Simulated earnings — returns and characteristics					
Theil (1)	0.34	0.32	0.39	0.34	0.00 (0%)
Theil (0)	0.28	0.27	0.35	0.28	0.00 (0%)

Table 5 (continued)

(v) Decomposition of earnings inequality among nonwhites by gender

	Total	Nonwhite Men	Nonwhite Women	Within	Between
Bolivia					
Observed earnings					
Theil (1)	0.59	0.53	0.69	0.57	0.02 (3%)
Theil (0)	0.75	0.69	0.82	0.73	0.02 (3%)
Simulated earnings — returns only					
Theil (1)	0.54	0.53	0.56	0.53	0.00 (1%)
Theil (0)	0.70	0.69	0.78	0.70	0.00 (0%)
Simulated earnings — returns and characteristics					
Theil (1)	0.62	0.53	0.81	0.62	0.01 (1%)
Theil (0)	0.77	0.69	0.98	0.76	0.01 (1%)
Brazil					
Observed earnings					
Theil (1)	0.52	0.51	0.50	0.51	0.01 (2%)
Theil (0)	0.46	0.45	0.44	0.45	0.01 (2%)
Simulated earnings — returns only					
Theil (1)	0.52	0.51	0.53	0.52	0.00 (0%)
Theil (0)	0.45	0.45	0.46	0.45	0.00 (0%)
Simulated earnings — returns and characteristics					
Theil (1)	0.51	0.51	0.51	0.51	0.00 (0%)
Theil (0)	0.45	0.45	0.46	0.45	0.00 (0%)
Guatemala					
Observed earnings					
Theil (1)	0.61	0.55	0.69	0.58	0.03 (5%)
Theil (0)	0.75	0.65	0.85	0.71	0.04 (5%)
Simulated earnings — returns only					
Theil (1)	0.55	0.55	0.48	0.55	0.00 (0%)
Theil (0)	0.65	0.65	0.68	0.65	0.00 (0%)
Simulated earnings — returns and characteristics					
Theil (1)	0.57	0.55	0.74	0.57	0.00 (0%)
Theil (0)	0.67	0.65	0.83	0.67	0.00 (0%)
Guyana					
Observed earnings					
Theil (1)	0.30	0.29	0.26	0.28	0.02 (7%)
Theil (0)	0.28	0.27	0.26	0.27	0.02 (5%)
Simulated earnings — returns only					
Theil (1)	0.30	0.29	0.32	0.29	0.00 (1%)
Theil (0)	0.28	0.27	0.35	0.28	0.00 (0%)
Simulated earnings — returns and characteristics					
Theil (1)	0.30	0.29	0.33	0.30	0.00 (0%)
Theil (0)	0.28	0.27	0.36	0.28	0.00 (0%)

Table 5 (continued)

(vi) Decomposition of earnings inequality among white men and nonwhite women

	Total	White Men	Nonwhite Women	Within	Between
Bolivia					
Observed earnings					
Theil (1)	0.63	0.47	0.69	0.52	0.12 (18%)
Theil (0)	0.79	0.52	0.82	0.66	0.13 (16%)
Simulated earnings — returns only					
Theil (1)	0.49	0.47	0.49	0.47	0.02 (6%)
Theil (0)	0.57	0.52	0.64	0.55	0.03 (6%)
Simulated earnings — returns and characteristics					
Theil (1)	0.52	0.47	0.62	0.51	0.01 (2%)
Theil (0)	0.61	0.52	0.74	0.60	0.01 (2%)
Brazil					
Observed earnings					
Theil (1)	0.67	0.60	0.50	0.59	0.08 (12%)
Theil (0)	0.63	0.56	0.44	0.52	0.11 (17%)
Simulated earnings — returns only					
Theil (1)	0.62	0.60	0.59	0.60	0.02 (3%)
Theil (0)	0.57	0.56	0.52	0.55	0.02 (4%)
Simulated earnings — returns and characteristics					
Theil (1)	0.62	0.60	0.66	0.61	0.01 (2%)
Theil (0)	0.57	0.56	0.57	0.56	0.01 (2%)
Guatemala					
Observed earnings					
Theil (1)	0.83	0.73	0.69	0.73	0.10 (12%)
Theil (0)	0.89	0.72	0.85	0.75	0.14 (16%)
Simulated earnings — returns only					
Theil (1)	0.74	0.73	0.44	0.73	0.01 (1%)
Theil (0)	0.74	0.72	0.63	0.72	0.02 (3%)
Simulated earnings — returns and characteristics					
Theil (1)	0.76	0.73	1.29	0.76	0.00 (0%)
Theil (0)	0.74	0.72	0.93	0.74	0.00 (0%)
Guyana					
Observed earnings					
Theil (1)	0.32	0.32	0.26	0.30	0.02 (6%)
Theil (0)	0.28	0.27	0.26	0.27	0.01 (4%)
Simulated earnings — returns only					
Theil (1)	0.33	0.32	0.41	0.33	0.00 (0%)
Theil (0)	0.28	0.27	0.43	0.28	0.00 (0%)
Simulated earnings — returns and characteristics					
Theil (1)	0.32	0.32	0.35	0.32	0.00 (0%)
Theil (0)	0.28	0.27	0.37	0.28	0.00 (0%)

Table 7: Theil index of overall per capita household earnings inequality decompositions

	Total	White Men	Nonwhite Men	White Women	Nonwhite Women	Within	Between
Bolivia							
Observed earnings							
Theil (1)	0.77	0.69	0.63	0.65	0.76	0.67	0.11 (14%)
Theil (0)	0.93	0.71	0.86	0.78	1.02	0.83	0.10 (11%)
Simulated earnings — returns only							
Theil (1)	0.57	0.47	0.50	0.67	0.40	0.50	0.07 (12%)
Theil (0)	0.71	0.60	0.67	0.78	0.46	0.65	0.07 (9%)
Simulated earnings — returns and characteristics							
Theil (1)	0.50	0.45	0.55	0.39	0.53	0.49	0.01 (2%)
Theil (0)	0.60	0.55	0.64	0.44	0.61	0.59	0.01 (2%)
Brazil							
Observed earnings							
Theil (1)	0.72	0.66	0.58	0.65	0.57	0.64	0.08 (11%)
Theil (0)	0.68	0.64	0.53	0.63	0.53	0.59	0.09 (13%)
Simulated earnings — returns only							
Theil (1)	0.72	0.67	0.62	0.67	0.62	0.66	0.06 (8%)
Theil (0)	0.69	0.65	0.58	0.65	0.59	0.62	0.07 (10%)
Simulated earnings — returns and characteristics							
Theil (1)	0.85	0.74	0.92	0.82	0.96	0.84	0.01 (1%)
Theil (0)	0.83	0.72	0.90	0.77	0.91	0.82	0.01 (1%)
Guatemala							
Observed earnings							
Theil (1)	0.87	0.83	0.62	0.55	0.75	0.77	0.10 (11%)
Theil (0)	0.97	0.91	0.77	0.82	0.80	0.85	0.12 (12%)
Simulated earnings — returns only							
Theil (1)	0.76	0.74	0.55	0.50	0.59	0.68	0.08 (11%)
Theil (0)	0.84	0.82	0.67	0.67	0.68	0.75	0.09 (11%)
Simulated earnings — returns and characteristics							
Theil (1)	0.79	0.74	0.92	0.82	0.75	0.77	0.02 (2%)
Theil (0)	0.86	0.81	0.79	0.83	0.76	0.83	0.03 (3%)
Guyana							
Observed earnings							
Theil (1)	0.37	0.33	0.42	0.31	0.30	0.36	0.01 (3%)
Theil (0)	0.35	0.30	0.41	0.33	0.35	0.35	0.01 (2%)
Simulated earnings — returns only							
Theil (1)	0.32	0.31	0.35	0.23	0.34	0.32	0.00 (0%)
Theil (0)	0.30	0.26	0.33	0.27	0.34	0.30	0.00 (0%)
Simulated earnings — returns and characteristics							
Theil (1)	0.33	0.31	0.36	0.20	0.51	0.33	0.01 (2%)
Theil (0)	0.31	0.26	0.37	0.28	0.49	0.30	0.01 (3%)

Table A-1: OLS log earnings regressions

(i) Bolivia

Variable label	White Men	Indigenous Men	White Women	Indigenous Women
Primary	0.40*	0.39**	0.57*	0.56**
	(0.20)	(0.12)	(0.22)	(0.16)
Secondary	0.66**	0.65**	0.97**	0.78**
	(0.20)	(0.13)	(0.24)	(0.18)
Tertiary	1.00**	0.92**	1.21**	1.17**
	(0.21)	(0.14)	(0.25)	(0.18)
Age	0.10**	0.05**	0.08**	0.07**
	(0.01)	(0.01)	(0.02)	(0.02)
Age^2	-0.001**	-0.001**	-0.001**	-0.001**
	(0.00)	(0.00)	(0.00)	(0.00)
Formal sector wage employee	0.61**	0.73**	0.66**	0.62**
	(0.12)	(0.10)	(0.16)	(0.19)
Informal sector wage employee	0.50**	0.75**	0.23	0.25*
	(0.09)	(0.07)	(0.14)	(0.12)
Public sector employee	0.29*	0.71**	0.42**	0.97**
	(0.12)	(0.09)	(0.13)	(0.12)
Urban	1.04**	1.22**	1.19**	1.08**
	(0.12)	(0.07)	(0.19)	(0.12)
Constant	2.83**	3.32**	2.58**	2.42**
	(0.29)	(0.25)	(0.43)	(0.40)
Number of Observations	923	1510	586	753
Adjusted R-squared	0.40	0.51	0.38	0.39

Standard errors in parentheses; ** significant at 99% level; * significant at 95% level

Table A-1 (continued)

(ii) Brazil

Variable label	White Men	Afro- Men	White Women	Afro- Women
1 year of schooling	0.10**	0.00	0.07	0.08
	(0.03)	(0.03)	(0.06)	(0.05)
2 years of schooling	0.05*	0.04	-0.03	0.08
	(0.03)	(0.12)	(0.05)	(0.04)
3 years of schooling	0.10**	0.05	-0.01	0.04
	(0.03)	(0.03)	(0.04)	(0.04)
4 years of schooling	0.20**	0.08**	0.07	0.05
	(0.03)	(0.03)	(0.04)	(0.04)
5 years of schooling	0.18**	0.06	0.03	0.06
	(0.03)	(0.03)	(0.05)	(0.05)
6 years of schooling	0.20**	0.08*	0.11	0.13**
	(0.03)	(0.04)	(0.06)	(0.05)
7 years of schooling	0.20**	0.06	0.10	0.06
	(0.04)	(0.04)	(0.06)	(0.06)
8 years of schooling	0.27**	0.07	0.17**	0.14*
	(0.04)	(0.04)	(0.06)	(0.06)
9 years of schooling	0.25**	0.05	0.18**	0.13*
	(0.04)	(0.05)	(0.07)	(0.07)
10 years of schooling	0.22**	0.06	0.20**	0.16*
	(0.05)	(0.05)	(0.07)	(0.07)
11 years of schooling	0.42**	0.17**	0.39**	0.28**
	(0.04)	(0.05)	(0.07)	(0.07)
12 years of schooling	0.52**	0.39**	0.61**	0.47**
	(0.06)	(0.09)	(0.08)	(0.11)
13 years of schooling	0.53**	0.30**	0.59**	0.57**
	(0.06)	(0.10)	(0.08)	(0.11)
14 years of schooling	0.53**	0.34**	0.72**	0.66**
	(0.07)	(0.09)	(0.09)	(0.11)
15 years of schooling	0.75**	0.45**	0.82**	0.78**
	(0.06)	(0.08)	(0.09)	(0.10)
16 years of schooling	0.78**	0.62**	1.02**	0.86**
	(0.07)	(0.10)	(0.10)	(0.12)
17 years of schooling	0.97**	0.64**	1.11**	1.07**
	(0.08)	(0.12)	(0.11)	(0.15)
Mother’s years of schooling	0.08**	0.06**	0.09**	0.07**
	(0.01)	(0.01)	(0.01)	(0.01)
Mother’s years of schooling^2	-0.005**	-0.003*	-0.006**	-0.003
	(0.00)	(0.00)	(0.00)	(0.002)
Age	0.08**	0.06**	0.05**	0.03**
	(0.00)	(0.00)	(0.00)	(0.00)
Age^2	-0.001**	-0.001**	-0.001**	-0.0004**
	(0.00)	(0.00)	(0.00)	(0.00)
Age*Schooling	0.001**	0.002**	0.001*	0.001**
	(0.00)	(0.00)	(0.00)	(0.00)
With labor card	0.04**	0.11**	0.19**	0.32**

	(0.01)	(0.01)	(0.02)	(0.02)
Without labor card	-0.30**	-0.20**	-0.20**	-0.01
	(0.01)	(0.01)	(0.02)	(0.02)
Public sector	-0.05**	0.14**	0.07**	0.28**
	(0.02)	(0.02)	(0.02)	(0.03)
Employer	0.62**	0.77**	0.91**	1.14**
	(0.02)	(0.04)	(0.04)	(0.08)
North	-0.17**	-0.10**	-0.13**	-0.08**
	(0.02)	(0.02)	(0.03)	(0.02)
Northeast	-0.44**	-0.39**	-0.52**	-0.48**
	(0.01)	(0.01)	(0.02)	(0.02)
South	-0.13**	-0.11**	-0.12**	-0.07**
	(0.01)	(0.02)	(0.01)	(0.03)
Center-West	-0.07**	0.02	-0.12**	-0.04*
	(0.02)	(0.01)	(0.02)	(0.02)
Urban	0.34**	0.29**	0.33**	0.36**
	(0.01)	(0.01)	(0.02)	(0.02)
Constant	3.68**	3.85**	3.69**	3.66**
	(0.05)	(0.06)	(0.09)	(0.08)
Number of Observations	32,417	26,507	19,750	14,251
Adjusted R-squared	0.50	0.44	0.50	0.46

Standard errors in parentheses; ** significant at 99% level; * significant at 95% level

Table A-1 (continued)

(iii) Guatemala

Variable label	White Men	Indigenous Men	White Women	Indigenous Women
Primary	0.40**	0.26**	0.31	0.22
	(0.07)	(0.07)	(0.17)	(0.13)
Secondary	0.53**	0.58**	0.39	0.45
	(0.10)	(0.12)	(0.20)	(0.23)
Tertiary	1.58**	0.96**	0.39	1.62*
	(0.26)	(0.20)	(0.46)	(0.82)
Mother's years of schooling	0.06**	0.05	0.02	0.05
	(0.01)	(0.03)	(0.02)	(0.03)
Age	0.04**	0.04**	0.08**	0.05**
	(0.01)	(0.01)	(0.03)	(0.02)
Age^2	-0.001**	-0.001**	-0.001**	-0.001**
	(0.00)	(0.00)	(0.00)	(0.00)
Formal sector wage employee	1.23**	1.66**	1.93**	1.86**
	(0.08)	(0.08)	(0.14)	(0.15)
Informal sector wage employee	0.98**	1.07**	1.18**	0.76**
	(0.07)	(0.07)	(0.13)	(0.10)
Public employee	1.36**	1.97**	2.24**	1.41**
	(0.10)	(0.15)	(0.19)	(0.41)
Guatemala City	-0.19*	-0.08	0.43*	0.28
	(0.10)	(0.33)	(0.17)	(0.20)
Rural	-0.45**	-0.36**	-0.29	-0.54**
	(0.06)	(0.08)	(0.17)	(0.12)
Constant	4.82**	4.60**	3.40**	4.18**
	(0.21)	(0.30)	(0.65)	(0.40)
Number of Observations	2795	1990	1363	906
Adjusted R-squared	0.41	0.35	0.30	0.21

Standard errors in parentheses; ** significant at 99% level; * significant at 95% level

Table A-1 (continued)

(iv) Guyana

Variable label	Indo- Men	Afro- Men	Indo- Women	Afro- Women
Primary	0.05	0.21	0.41**	0.12
	(0.08)	(0.14)	(0.14)	(0.24)
Secondary	0.21*	0.34*	0.71**	0.34
	(0.10)	(0.15)	(0.16)	(0.24)
Tertiary	0.54**	0.68**	1.30**	0.71**
	(0.15)	(0.16)	(0.32)	(0.25)
Age	0.09**	0.06**	0.04*	0.03
	(0.01)	(0.01)	(0.02)	(0.01)
Age^2	-0.001**	-0.001**	-0.001*	0.000
	(0.00)	(0.00)	(0.00)	(0.00)
Employee	-0.03	0.02	0.03	0.31**
	(0.06)	(0.06)	(0.10)	(0.08)
Georgetown	0.03	-0.03	0.53**	0.53**
	(0.12)	(0.08)	(0.19)	(0.10)
Rural	-0.07	-0.22**	0.26	0.31**
	(0.10)	(0.08)	(0.17)	(0.10)
Constant	8.34**	8.68**	7.89**	8.16**
	(0.27)	(0.27)	(0.45)	(0.35)
Number of Observations	866	720	279	481
Adjusted R-squared	0.08	0.13	0.16	0.20

Standard errors in parentheses; ** significant at 99% level; * significant at 95% level

Table A-2: Simulated v. actual years of schooling and employment sector, Brazil

(i) Simulated v. actual years of schooling

Nonwhite men

Actual years of schooling	Simulated years of schooling																		
	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	Total
0	6316	133	171	234	684	75	99	54	205	46	50	274	12	10	13	64	30	3743	12213
1	5	1155	3	16	59	14	17	14	44	11	17	58	4	3	4	18	7	378	1827
2	8	8	1823	28	135	46	38	32	74	26	35	138	6	2	10	28	15	676	3128
3	1	3	1	2401	94	33	30	33	94	44	37	138	9	9	7	44	21	894	3893
4	2	2	0	5	4902	31	35	41	115	64	58	213	17	18	18	71	54	1548	7194
5	0	0	0	1	23	1990	12	28	70	45	51	139	14	16	18	31	17	707	3162
6	0	0	0	2	12	3	1452	5	37	23	29	115	10	11	5	24	15	442	2185
7	0	1	0	3	25	3	4	1498	46	25	34	125	4	12	12	37	18	512	2359
8	0	0	0	1	30	0	0	0	2960	12	20	111	16	16	22	60	32	1009	4289
9	0	0	0	1	5	0	2	0	9	794	6	33	8	5	9	18	12	199	1101
10	0	1	0	0	11	0	1	0	12	1	823	37	5	4	11	18	10	228	1162
11	0	0	0	0	1	0	0	0	1	0	4	3201	10	12	20	51	43	890	4233
12	0	0	0	0	0	0	0	0	0	0	0	1	124	1	2	3	1	22	154
13	0	0	1	0	1	0	0	0	0	0	0	1	0	155	1	5	1	27	192
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	149	1	0	32	182
15	0	0	0	0	0	0	0	0	0	0	0	0	1	1	5	421	6	63	497
16	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	238	40	280
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	1	103	106
Tota	6332	1303	1999	2692	5982	2195	1690	1705	3667	1091	1165	4584	240	275	309	894	521	11513	48157

White Women

Actual years of schooling	Simulated years of schooling																		
	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	Total
0	4575	97	41	110	267	19	17	26	71	0	9	52	2	3	1	19	28	3737	9074
1	0	805	0	5	14	2	2	4	9	0	0	5	0	1	1	5	8	282	1143
2	31	21	1791	16	54	3	8	5	18	1	5	21	1	0	1	8	10	549	2543
3	48	27	10	2871	45	4	4	9	24	1	2	26	3	3	2	12	22	1004	4117
4	98	67	28	20	7898	43	32	24	72	4	27	44	7	7	1	44	96	2494	11006
5	41	14	6	11	8	2060	2	6	6	1	3	4	0	1	0	5	9	611	2788
6	21	11	2	5	6	6	1648	1	7	1	2	4	0	1	0	1	5	514	2235
7	36	21	9	16	12	17	8	1801	5	5	5	2	0	0	0	1	5	496	2439
8	33	32	15	24	24	33	28	21	4539	4	4	16	4	4	1	10	49	1274	6115
9	17	12	10	6	19	37	12	17	23	1124	5	5	1	1	0	2	9	267	1567
10	18	10	10	8	16	37	49	38	37	19	1513	0	3	2	2	0	8	326	2096
11	86	47	40	60	117	122	112	124	214	60	76	7146	12	23	21	59	188	1715	10222
12	5	0	3	2	5	9	13	9	14	9	11	6	452	2	5	0	4	93	642
13	4	2	3	4	3	5	15	5	14	2	6	2	0	590	0	1	3	99	758
14	4	3	3	6	21	17	10	10	40	5	8	27	5	6	629	6	21	113	934
15	24	7	6	17	50	27	21	36	95	13	37	117	15	32	13	2096	80	409	3095
16	2	0	0	1	2	6	2	3	10	2	3	0	2	2	2	0	918	138	1093
17	2	0	0	1	1	3	0	0	2	1	0	0	1	0	1	0	3	388	403
Tota	5045	1176	1977	3183	8562	2450	1983	2139	5200	1252	1716	7477	508	678	680	2269	1466	14509	62270

Nonwhite Women

Actual years of schooling	Simulated years of schooling																		
	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	Total
0	6023	161	164	240	811	32	48	35	180	13	25	188	11	9	18	63	38	4236	12295
1	0	1028	1	4	47	1	5	4	14	0	2	26	2	2	1	4	12	365	1518
2	30	11	1795	22	126	19	16	13	57	11	16	63	5	3	8	21	17	684	2917
3	56	30	17	2429	97	19	20	25	60	12	16	79	5	6	11	32	27	958	3899
4	84	15	8	11	5020	41	24	13	52	16	24	101	17	11	10	66	51	1706	7270
5	33	16	2	6	29	1974	8	3	29	4	4	37	5	5	11	16	19	815	3016
6	23	10	2	2	4	14	1400	4	25	11	8	30	7	5	3	15	20	515	2098
7	23	11	5	3	8	6	3	1562	23	7	12	26	9	9	1	11	11	617	2347
8	19	7	1	0	3	2	0	0	3031	3	10	40	9	16	7	28	34	947	4157
9	11	4	1	1	9	0	1	6	17	890	8	23	5	8	5	13	10	262	1274
10	10	4	0	1	1	18	5	6	21	8	988	23	9	3	8	8	15	302	1430
11	54	22	4	8	31	17	20	15	59	6	14	3967	20	37	24	65	72	1187	5622
12	0	0	0	0	0	0	0	0	1	0	0	0	141	4	1	1	3	21	172
13	0	1	0	1	1	0	0	0	0	0	0	0	0	140	1	1	0	39	184
14	0	0	0	0	0	0	0	0	0	0	0	0	0	2	214	3	3	33	255
15	5	0	0	1	1	0	0	1	1	0	0	0	0	5	2	581	20	89	706
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	178	32	210
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	73	74
Tota	6371	1320	2000	2729	6188	2143	1550	1687	3570	981	1127	4603	245	265	325	929	530	12881	49444

Table A-2 (continued)

(i) Simulated v. actual employment sector

Nonwhite men

	Simulated occupation					
	Non income earner	Self Employed	With Labor Card	W/out Labor card	Public Sector	Employer
actual occupation	0.8627	0.0329	0.0378	0.0486	0.0035	0.0144
	0.0055	0.9294	0.0224	0.0285	0.0018	0.0124
	0.0063	0.0187	0.9441	0.0172	0.0004	0.0133
	0.0123	0.0276	0.0235	0.9258	0.0020	0.0088
	0.0172	0.0521	0.0736	0.0601	0.7709	0.0261
	0.0020	0.0201	0.0322	0.0402	0.0040	0.9015

	Simulated occupation						
	Non income earner	Self Employed	With Labor Card	W/out Labor card	Public Sector	Employer	Total
actual occupation	10631	406	466	599	43	178	12323
	56	9457	228	290	18	126	10175
	74	220	11086	202	5	156	11743
	115	257	219	8632	19	82	9324
	37	112	158	129	1656	56	2148
	2	20	32	40	4	897	995
Total	10915	10472	12189	9892	1745	1495	46708

White Women

	Simulated occupation					
	Non income earner	Self Employed	With Labor Card	W/out Labor card	Public Sector	Employer
actual occupation	0.4309	0.1602	0.2428	0.1284	0.0138	0.0239
	0.0000	0.9212	0.0625	0.0114	0.0000	0.0049
	0.0057	0.0253	0.9463	0.0080	0.0048	0.0099
	0.0010	0.0354	0.0720	0.8774	0.0033	0.0108
	0.0114	0.0925	0.1968	0.0631	0.5989	0.0373
	0.0000	0.0279	0.1611	0.0440	0.0043	0.7626

	Simulated occupation						
	Non income earner	Self Employed	With Labor Card	W/out Labor card	Public Sector	Employer	Total
actual occupation	15697	5834	8845	4677	503	871	36427
	0	4523	307	56	0	24	4910
	53	234	8757	74	44	92	9254
	6	203	413	5031	19	62	5734
	38	308	655	210	1993	124	3328
	0	26	150	41	4	710	931
Total	15794	11128	19127	10089	2563	1883	60584

Nonwhite women

	Simulated occupation					
	Non income earner	Self Employed	With Labor Card	W/out Labor card	Public Sector	Employer
actual occupation	0.4323	0.1732	0.2097	0.1511	0.0111	0.0226
	0.0000	0.9397	0.0435	0.0085	0.0000	0.0083
	0.0044	0.0375	0.9365	0.0044	0.0024	0.0147
	0.0020	0.0518	0.0919	0.8385	0.0031	0.0127
	0.0235	0.1278	0.1691	0.0682	0.5644	0.0471
	0.0000	0.0130	0.0433	0.0173	0.0000	0.9264

	Simulated occupation						
	Non income earner	Self Employed	With Labor Card	W/out Labor card	Public Sector	Employer	Total
actual occupation	12740	5105	6179	4454	326	667	29471
	0	3756	174	34	0	33	3997
	26	219	5472	26	14	86	5843
	13	335	594	5419	20	82	6463
	49	266	352	142	1175	98	2082
	0	3	10	4	0	214	231
Total	12828	9684	12781	10079	1535	1180	48087

Table A-3: Multinomial logits for education, number of children, and sector

(i) Bolivia

Educational Multinomial

	White Men		(N=616)	***Nonwhite Men***		(N=1000)	***White Women***		(N=645)	***Nonwhite Women***		(N=1114)
Variable	Primary	Secondary	Tertiary	Primary	Secondary	Tertiary	Primary	Secondary	Tertiary	Primary	Secondary	Tertiary
Age	0.108	0.013	0.076	-0.021	-0.135*	-0.020	-0.202*	-0.336**	-0.232*	-0.050	-0.282**	-0.067
	(0.079)	(0.082)	(0.084)	(0.049)	(0.058)	(0.068)	(0.087)	(0.089)	(0.106)	(0.038)	(0.043)	(0.057)
Age^2	-0.001	-0.001	-0.001	-0.000	0.000	-0.001	0.001	0.002**	0.001	-0.000	0.002**	-0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
Chuquisaca	-17.331**	-16.400**	-16.917**	-17.537**	-17.961**	1.204	0.072	-1.404	-0.876	-16.724**	2.570**	3.469**
	(1.703)	(1.972)	(1.576)	(1.810)	(1.306)	(1.495)	(1.282)	(2.030)	(1.671)	(0.888)	(0.934)	(0.873)
La Paz	-17.209**	-15.382**	-16.897	-16.539**	-16.385**	2.261	0.622	-0.784	-0.702	-14.883**	4.675**	4.073**
	(0.758)	(1.181)	(.)	(1.816)	(1.284)	(1.574)	(1.273)	(1.997)	(1.654)	(0.831)	(0.853)	(0.854)
Cochabamba	-18.828**	-17.069**	-18.375**	-16.093**	-16.815**	2.509	1.499	0.307	-0.013	-14.955**	3.908**	4.319**
	(1.599)	(1.838)	(1.438)	(1.836)	(1.320)	(1.577)	(1.205)	(1.967)	(1.649)	(0.906)	(0.924)	(0.895)
Oruro	-18.917**	-16.551**	-17.629**	-16.681**	-16.449**	2.639	0.370	-1.186	-0.390	-15.522**	4.644**	4.822**
	(1.588)	(1.840)	(1.406)	(1.905)	(1.417)	(1.558)	(1.269)	(1.998)	(1.653)	(0.895)	(0.906)	(0.923)
Potosi	-0.489	1.531	0.116	-16.698**	-17.180**	1.996	0.042	-1.251	-0.375	-15.828**	3.844**	3.435**
	(1.014)	(.)	(1.192)	(1.820)	(1.291)	(1.553)	(1.252)	(1.979)	(1.624)	(0.862)	(0.868)	(0.845)
Tarija	-21.194**	-18.793**	-20.700**	-18.553**	-19.785	-0.082	0.904	-0.976	-0.639	-15.679**	3.780	4.274**
	(1.451)	(1.713)	(1.247)	(1.526)	(.)	(1.826)	(1.330)	(2.114)	(1.725)	(0.967)	(.)	(1.036)
Santa Cruz	-19.344**	-17.859**	-20.003**	-17.506**	-17.652**	1.787	1.031	-0.351	-0.583	-15.590**	4.906**	4.112**
	(1.394)	(1.672)	(1.218)	(1.840)	(1.328)	(1.632)	(1.230)	(1.973)	(1.621)	(0.903)	(0.941)	(0.983)
Beni	-20.117**	-18.070**	-20.497**	-16.629**	-16.943**	2.199	1.922	0.916	0.414	-15.504**	5.486**	4.550
	(1.472)	(1.741)	(1.344)	(1.890)	(1.393)	(1.578)	(1.348)	(2.046)	(1.737)	(0.979)	(0.983)	(.)
Urban	0.920	2.138**	3.195**	1.282**	2.758**	2.813**	2.141**	4.026**	4.240**	1.333**	2.225**	2.712**
	(0.591)	(0.613)	(0.695)	(0.313)	(0.358)	(0.411)	(0.502)	(0.574)	(0.708)	(0.210)	(0.290)	(0.420)
Constant	19.870**	19.669**	18.644**	19.950**	21.399**	-0.569	6.464*	9.030**	6.448*	18.261	1.201	-3.335*
	(2.020)	(2.241)	(1.981)	(2.142)	(1.783)	(.)	(2.614)	(3.023)	(2.982)	(.)	(1.242)	(1.449)

Demographic Multinomial

	White Women		(N=976)			***Nonwhite Women***		(N=1686)		
Variable	1 children	2 children	3 children	4 children	> 4 children	1 children	2 children	3 children	4 children	> 4 children
Age	-0.056	0.028	0.003	0.516**	0.722**	-0.026	-0.016	0.184*	0.403**	0.778**
	(0.054)	(0.080)	(0.116)	(0.189)	(0.271)	(0.047)	(0.056)	(0.084)	(0.141)	(0.216)
Age^2	0.000	-0.002	-0.001	-0.009**	-0.012**	-0.000	-0.001	-0.004**	-0.007**	-0.012**
	(0.001)	(0.001)	(0.001)	(0.003)	(0.004)	(0.000)	(0.001)	(0.001)	(0.002)	(0.003)
Primary	0.469	0.055	-0.082	-0.173	-0.980	0.040	0.251	-0.298	0.099	0.093
	(0.420)	(0.465)	(0.436)	(0.951)	(0.665)	(0.238)	(0.256)	(0.265)	(0.303)	(0.361)
Secondary	0.463	-0.436	-0.940	-0.868	-2.266**	-0.309	-0.334	-1.079**	-1.210*	-1.684*
	(0.480)	(0.515)	(0.518)	(1.090)	(0.832)	(0.376)	(0.379)	(0.406)	(0.490)	(0.742)
University	-0.066	-0.818	-1.379*	-3.683**	-34.006**	-0.227	-0.309	-1.700**	-2.095**	-2.351*
	(0.484)	(0.516)	(0.561)	(1.273)	(0.724)	(0.347)	(0.375)	(0.453)	(0.591)	(1.081)
Urban	0.134	-0.201	-0.529	-1.010	-1.213*	0.083	-0.430*	-0.380	-0.806**	-1.570**
	(0.346)	(0.344)	(0.366)	(0.605)	(0.522)	(0.204)	(0.209)	(0.223)	(0.263)	(0.330)
Constant	1.748	1.830	2.274	-6.605	-8.639	1.895	2.422*	-0.705	-4.796	-11.309**
	(1.282)	(1.646)	(2.257)	(3.141)*	(4.688)	(1.156)	(1.215)	(1.632)	(2.490)	(3.770)

Occupational Multinomial

	White Men		(N=1363)		***Nonwhite Men***		(N=2016)		***White Women***		(N=1507)		***Nonwhite Women***		(N=2107)	
Variable	Informal	Public	Self-empl	Nonearner	Informal	Public	Self-empl	Nonearner	Informal	Public	Self-empl	Nonearner	Informal	Public	Self-empl	Nonearner
Primary	1.750	18.239**	0.596	1.054	0.499	18.637**	0.309	1.279	-15.663**	3.957	-16.528**	-16.378**	3.721**	2.881	3.255*	3.010*
	(1.298)	(2.228)	(1.264)	(1.316)	(0.836)	(1.825)	(0.800)	(0.919)	(2.576)	(.)	(2.419)	(2.431)	(1.573)	(1.742)	(1.535)	(1.535)
Secondary	1.042	19.199**	-0.019	0.596	-0.931	18.485**	-0.863	-0.056	-17.541**	3.856**	-19.207**	-18.529**	0.924	2.735*	-0.296	-0.263
	(1.272)	(2.217)	(1.239)	(1.289)	(0.851)	(1.788)	(0.816)	(0.961)	(2.707)	(1.124)	(2.509)	(2.533)	(1.214)	(1.386)	(1.142)	(1.133)
University	0.129	19.705**	-0.826	0.242	-1.293	19.067**	-2.293**	-0.042	-17.327**	4.620**	-20.439**	-19.340**	0.451	2.649	-2.067	-1.726
	(1.261)	(2.158)	(1.222)	(1.268)	(0.884)	(1.725)	(0.858)	(1.003)	(2.569)	(1.140)	(2.393)	(2.412)	(1.209)	(1.467)	(1.150)	(1.131)
Age	-0.150	0.215*	-0.152	-0.443**	-0.132	0.054	-0.091	-0.346**	-0.253	0.253	-0.240*	-0.484**	-0.288	-0.188	-0.296	-0.513*
	(0.084)	(0.105)	(0.084)	(0.083)	(0.074)	(0.093)	(0.072)	(0.073)	(0.143)	(0.162)	(0.120)	(0.116)	(0.208)	(0.213)	(0.203)	(0.201)
Age^2	0.002	-0.002	0.002*	0.006**	0.001	-0.001	0.001	0.004**	0.003	-0.003	0.003*	0.006**	0.004	0.002	0.004	0.006**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.003)	(0.002)	(0.002)
Average age of hh	0.002	0.012	0.007	0.025	0.051*	0.052*	0.063**	0.068**	-0.018	0.024	0.002	0.015	0.048	0.023	0.027	0.033
	(0.023)	(0.023)	(0.023)	(0.024)	(0.020)	(0.024)	(0.020)	(0.021)	(0.027)	(0.024)	(0.023)	(0.020)	(0.044)	(0.048)	(0.042)	(0.042)
average # in hh w/no ed	1.863	3.808	2.552	-0.036	-2.342	-3.834*	-3.146*	-3.770*	-0.559	-1.825	-2.313	-1.980	98.559	98.501**	100.359**	101.487**
	(1.879)	(2.029)	(1.914)	(2.017)	(1.484)	(1.658)	(1.470)	(1.512)	(1.841)	(1.875)	(1.506)	(1.436)	(.)	(2.005)	(1.243)	(1.242)
average # in hh w/pr ed	0.226	0.108	0.673	-1.441	-1.662	-2.671*	-2.691*	-3.075*	1.423	-1.243	0.044	0.494	19.613	21.189**	21.328	22.156
	(0.978)	(1.108)	(1.066)	(1.103)	(1.279)	(1.328)	(1.306)	(1.314)	(1.658)	(1.727)	(1.459)	(1.455)	(.)	(8.105)	(14.299)	(.)
average # in hh w/sec ed	-0.576	0.005	0.119	-1.189	-2.157	-2.907*	-2.770*	-3.189*	0.669	-0.024	0.149	0.623	18.008	20.065	19.894	20.393**
	(0.848)	(1.011)	(0.942)	(0.948)	(1.209)	(1.245)	(1.215)	(1.250)	(1.499)	(1.571)	(1.323)	(1.334)	(.)	(.)	(.)	(4.727)
average # in hh w/ter ed	-1.288	-0.948	-0.788	-1.491	-2.337*	-2.453*	-2.888*	-2.744*	-0.187	-0.653	-0.799	-0.105	16.500	20.059	19.405	20.093
	(0.939)	(1.022)	(1.024)	(1.093)	(1.191)	(1.236)	(1.228)	(1.231)	(1.467)	(1.496)	(1.245)	(1.243)	(.)	(.)	(.)	(11.584)
Number of children in hh	-0.076	-0.187	-0.035	-0.277*	-0.068	0.019	-0.050	-0.130	0.146	0.116	0.099	0.122	0.214	-0.212	0.117	0.113
	(0.115)	(0.154)	(0.119)	(0.124)	(0.110)	(0.132)	(0.106)	(0.119)	(0.173)	(0.190)	(0.158)	(0.151)	(0.202)	(0.231)	(0.194)	(0.191)
Number of teens in hh	-0.024	-0.078	-0.255	0.013	0.231	0.291	0.170	0.381*	0.205	0.360	0.085	0.191	-0.424	-0.188	-0.470	-0.292
	(0.171)	(0.218)	(0.172)	(0.179)	(0.174)	(0.193)	(0.168)	(0.179)	(0.243)	(0.278)	(0.230)	(0.208)	(0.264)	(0.263)	(0.240)	(0.234)
Number of adults in hh	0.041	0.018	-0.062	0.163	0.117	0.078	0.094	0.086	-0.091	0.045	0.139	0.159	0.248	0.295	0.104	0.240
	(0.160)	(0.179)	(0.158)	(0.162)	(0.178)	(0.209)	(0.172)	(0.185)	(0.190)	(0.189)	(0.177)	(0.165)	(0.505)	(0.520)	(0.498)	(0.495)
Number of elderly in hh	-0.683	-0.870	-0.590	-0.893	-0.496	-0.250	0.201	0.054	0.337	-0.753	-0.089	-0.160	-2.777**	-1.765	-2.052*	-2.302*
	(0.453)	(0.473)	(0.450)	(0.462)	(0.492)	(0.582)	(0.447)	(0.471)	(0.549)	(0.614)	(0.533)	(0.513)	(1.012)	(0.954)	(0.944)	(0.940)
Household head	-0.553	-1.023	0.009	-1.706**	-0.739	-0.323	0.697	-2.440**	-0.013	1.451	1.799	0.636	19.837	22.398**	21.747*	19.927
	(0.563)	(0.602)	(0.580)	(0.591)	(0.678)	(0.808)	(0.684)	(0.676)	(1.111)	(0.981)	(0.979)	(0.926)	(.)	(7.786)	(9.447)	(.)
Spouse	-1.147	-2.600	-0.055	-1.942	-1.845	-5.345**	-1.753	-3.481*	-0.356	0.593	1.255*	1.070*	-0.137	1.474	1.100	0.857
	(1.227)	(1.566)	(1.399)	(1.889)	(1.256)	(1.479)	(1.174)	(1.438)	(0.642)	(0.649)	(0.570)	(0.530)	(0.902)	(1.199)	(0.876)	(0.843)
Urban	-0.614	-0.871	-1.847*	-1.340	-0.723	-1.725**	-2.387**	-1.468*	0.089	-2.075	-0.587	-1.187	-18.104	-20.297	-18.634**	-19.252**
	(0.823)	(0.980)	(0.813)	(0.820)	(0.572)	(0.629)	(0.549)	(0.586)	(1.205)	(1.276)	(1.134)	(1.118)	(12.971)	(.)	(2.981)	(2.982)
Constant	4.511*	-23.219	4.919*	10.526**	6.487**	-17.021	6.250**	10.913**	22.584**	-8.701**	24.194	28.897**	3.812	0.041	4.856*	9.593**
	(2.012)	(.)	(2.002)	(2.032)	(1.607)	(.)	(1.606)	(1.649)	(2.316)	(3.231)	(.)	(0.878)	(2.232)	(0.000)	(2.088)	(2.022)

Standard errors in parentheses; ** significant at 99% level; * significant at 95% level

Table A-3 (continued)

(ii) Brazil

Educational Multinomial

Variable	***White Men*** (N=43,303)	***Nonwhite Men*** (N=36,820)	***White Women*** (N=48,285)	***Nonwhite Women*** (N=36,736)
Age				
Age^2		See Table A-2 (i);		
Mother's years of schooling		full results		
Mother's years of schooling^2		for all		
North		18 categories		
Northeast		by race-gender group		
South		available		
Center-West		upon		
Urban		request		
Constant				

Demographic Multinomial

	White Women		(N=38,989)			***Nonwhite Women***		(N=28,443)		
Variable	1 children	2 children	3 children	4 children	> 4 children	1 children	2 children	3 children	4 children	> 4 children
Age	0.077**	0.301**	0.422**	0.491**	0.623**	0.048**	0.164**	0.254**	0.380**	0.551**
	(0.009)	(0.015)	(0.026)	(0.040)	(0.059)	(0.008)	(0.011)	(0.016)	(0.022)	(0.031)
Age^2	-0.002**	-0.004**	-0.006**	-0.007**	-0.008**	-0.001**	-0.002**	-0.004**	-0.005**	-0.007**
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Years of schooling	-0.034**	-0.048**	-0.097**	-0.192**	-0.278**	-0.015**	-0.026**	-0.065**	-0.142**	-0.222**
	(0.004)	(0.005)	(0.006)	(0.011)	(0.017)	(0.006)	(0.006)	(0.007)	(0.010)	(0.012)
Mother's years of schooling	-0.056**	-0.054**	-0.078**	-0.188**	-0.241**	-0.044**	-0.073**	-0.111**	-0.124**	-0.253**
	(0.011)	(0.011)	(0.015)	(0.034)	(0.055)	(0.017)	(0.017)	(0.022)	(0.034)	(0.046)
North	0.544**	0.846**	1.056**	1.624**	1.703**	0.188**	0.469**	0.825**	1.054**	1.792**
	(0.103)	(0.108)	(0.126)	(0.169)	(0.221)	(0.075)	(0.076)	(0.084)	(0.107)	(0.108)
Northeast	0.329**	0.501**	0.745**	1.196**	1.541**	0.092*	0.272**	0.429**	0.607**	0.932**
	(0.049)	(0.052)	(0.064)	(0.092)	(0.113)	(0.045)	(0.047)	(0.055)	(0.073)	(0.081)
South	0.083*	0.036	-0.014	0.019	-0.135	-0.098	-0.005	0.049	0.045	-0.213
	(0.035)	(0.038)	(0.051)	(0.088)	(0.124)	(0.084)	(0.086)	(0.102)	(0.138)	(0.176)
Center-West	0.065	0.256**	0.394**	0.235*	0.100	-0.071	0.105	0.105	0.026	-0.269*
	(0.052)	(0.053)	(0.067)	(0.120)	(0.172)	(0.061)	(0.061)	(0.072)	(0.100)	(0.126)
Urban	-0.020	-0.094	-0.191**	-0.351**	-0.696**	-0.013	-0.066	-0.243**	-0.409**	-0.636**
	(0.048)	(0.050)	(0.061)	(0.086)	(0.099)	(0.052)	(0.053)	(0.059)	(0.072)	(0.073)
Constant	-0.199	-4.051**	-6.641**	-8.420**	-11.210**	-0.087	-1.979**	-3.801**	-6.637**	-9.861**
	(0.178)	(0.273)	(0.464)	(0.719)	(1.079)	(0.189)	(0.225)	(0.310)	(0.420)	(0.574)

Standard errors in parentheses; ** significant at 99% level; * significant at 95% level

Occupational Multinomial

Variable	***White Men*** (N=52,927)	***Nonwhite Men*** (N=46,683)	***White Women*** (N=60,562)	***Nonwhite Women*** (N=48,053)
Years of schooling				
Years of schooling^2		See Table A-2 (ii);		
Age		full results		
Age^2		for all		
Age*years of schooling		5 categories		
Average age of hh		by race-gender group		
Average schooling of hh		available		
Number of children in hh		upon		
Number of adults in hh		request		
Number of elderly in hh				
Household head				
Spouse				
No head				
North				
Northeast				
South				
Center-West				
Urban				
Constant				

Table A-3 (continued)

(iii) Guatemala
Educational Multinomial

	White Men		(N=3381)	***Nonwhite Men***		(N=2374)	***White Women***		(N=4205)	***Nonwhite Women***		(N=3035)
Variable	Primary	Secondary	Tertiary	Primary	Secondary	Tertiary	Primary	Secondary	Tertiary	Primary	Secondary	Tertiary
Age	-0.042	-0.124**	0.135	-0.047*	0.054	0.299	-0.067**	-0.074*	0.315**	-0.082**	-0.183**	0.048
	(0.022)	(0.035)	(0.075)	(0.022)	(0.081)	(0.208)	(0.016)	(0.030)	(0.121)	(0.020)	(0.059)	(0.089)
Age^2	-0.000	0.001	-0.002**	0.000	-0.002	-0.005*	0.000	-0.000	-0.005**	0.000	0.001	-0.001
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.002)	(0.000)	(0.000)	(0.002)	(0.000)	(0.001)	(0.001)
Mother's years of schooling	0.345**	0.546**	0.764**	0.641**	0.823**	0.955**	0.314**	0.581**	0.793**	0.385**	0.578**	0.678**
	(0.047)	(0.051)	(0.060)	(0.139)	(0.154)	(0.181)	(0.045)	(0.053)	(0.060)	(0.096)	(0.110)	(0.134)
Guatemala City	0.200	-0.099	-0.715	0.288	-0.080	1.328	-0.376*	-0.660*	-1.061	0.188	-0.649	-40.915**
	(0.234)	(0.304)	(0.624)	(0.566)	(0.815)	(1.273)	(0.175)	(0.274)	(0.655)	(0.603)	(1.163)	(0.777)
Rural	-0.657**	-2.136**	-3.411**	-0.879**	-2.302**	-4.618**	-1.017**	-2.650**	-2.604**	-0.826**	-3.478**	-3.090*
	(0.162)	(0.214)	(0.446)	(0.178)	(0.364)	(1.118)	(0.114)	(0.208)	(0.427)	(0.141)	(0.411)	(1.253)
Constant	2.914**	4.161**	-3.461*	2.528**	-0.051	-6.952	2.943**	2.169**	-7.956**	2.190**	2.735*	-4.141
	(0.532)	(0.736)	(1.622)	(0.504)	(1.326)	(4.566)	(0.371)	(0.610)	(2.221)	(0.418)	(1.076)	(2.175)

Demographic Multinomial

	White Women		(N=3519)			***Nonwhite Women***		(N=2436)		
Variable	1 children	2 children	3 children	4 children	> 4 children	1 children	2 children	3 children	4 children	> 4 children
Age	-0.151**	-0.163**	-0.138**	-0.033	0.220*	-0.066	-0.106*	0.005	0.412**	0.474**
	(0.031)	(0.034)	(0.040)	(0.062)	(0.105)	(0.046)	(0.053)	(0.067)	(0.101)	(0.107)
Age^2	0.001**	0.001*	0.000	-0.001	-0.005**	0.000	0.000	-0.001	-0.007**	-0.008**
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Primary	-0.140	-0.192	-0.477*	-0.458*	-0.658**	0.218	-0.086	-0.143	-0.586*	-0.764**
	(0.183)	(0.185)	(0.186)	(0.211)	(0.220)	(0.246)	(0.255)	(0.255)	(0.253)	(0.247)
Secondary	-0.437	-0.641*	-0.767*	-0.968	-0.869	0.138	-0.977	-1.207	-1.967*	-1.580*
	(0.285)	(0.306)	(0.309)	(0.735)	(0.831)	(0.569)	(0.693)	(0.669)	(0.813)	(0.786)
University	0.109	-0.058	-1.398	-1.572	-0.850	1.367	0.953	-44.689	-44.715	-44.342
	(0.576)	(0.687)	(0.775)	(1.150)	(0.948)	(1.100)	(1.029)	(.)	(.)	(.)
Mother's years of schooling	-0.012	-0.028	-0.052	-0.190**	-0.205*	-0.067	-0.083	-0.165	-0.117	-0.199
	(0.029)	(0.035)	(0.037)	(0.073)	(0.086)	(0.074)	(0.077)	(0.106)	(0.089)	(0.129)
Guatemala City	-0.061	0.137	-0.093	0.254	0.095	0.702	0.599	1.145	1.418	0.980
	(0.254)	(0.268)	(0.313)	(0.381)	(0.457)	(0.938)	(0.955)	(0.898)	(1.013)	(1.060)
Rural	-0.004	0.292	0.610**	0.791**	1.023**	0.719**	0.873**	0.745**	1.034**	1.278**
	(0.184)	(0.179)	(0.192)	(0.239)	(0.328)	(0.234)	(0.238)	(0.268)	(0.266)	(0.246)
Constant	5.058**	5.600**	5.361**	2.904*	-1.532	2.156	3.702**	2.156	-4.938**	-6.363**
	(0.794)	(0.813)	(0.913)	(1.202)	(2.046)	(1.130)	(1.245)	(1.447)	(1.880)	(2.000)

Occupational Multinomial

	White Men		(N=4790)		***Nonwhite Men***		(N=3341)		***White Women***		(N=5471)		***Nonwhite Women***		(N=3781)	
Variable	Informal	Public	Self-empl	Nonearner	Informal	Public	Self-empl	Nonearner	Informal	Public	Self-empl	Nonearner	Informal	Public	Self-empl	Nonearner
Primary	-0.403*	1.167**	-0.237	-0.376	-0.394	0.015	-0.292	-0.488*	-1.342**	-0.296	-1.407**	-1.328**	-1.070	-0.170	-0.506	-1.052
	(0.183)	(0.378)	(0.184)	(0.204)	(0.218)	(0.510)	(0.220)	(0.236)	(0.324)	(0.763)	(0.307)	(0.295)	(0.655)	(0.876)	(0.642)	(0.612)
Secondary	-0.743**	1.344**	-0.293	-0.013	-0.991*	1.274	-1.184*	-0.479	-2.265**	0.599	-1.791**	-1.597**	-0.717	1.518	-0.092	-0.634
	(0.246)	(0.495)	(0.248)	(0.248)	(0.490)	(0.789)	(0.534)	(0.470)	(0.408)	(0.786)	(0.393)	(0.365)	(1.080)	(1.606)	(1.057)	(1.004)
University	-1.734**	1.547**	-0.943*	-0.754*	-2.725*	3.256**	-1.576*	-1.476*	-2.434**	1.467	-1.916**	-2.288**	509.228	-552.763	916.862	474.418
	(0.379)	(0.582)	(0.384)	(0.363)	(1.061)	(0.919)	(0.768)	(0.650)	(0.504)	(0.803)	(0.553)	(0.469)	(.)	(.)	(.)	(.)
Age	-0.090**	0.009	0.042	-0.173**	-0.114*	-0.017	-0.032	-0.222**	-0.106	0.054	-0.103	-0.290**	-0.112	0.224	-0.060	-0.181*
	(0.031)	(0.044)	(0.032)	(0.032)	(0.046)	(0.086)	(0.049)	(0.047)	(0.057)	(0.097)	(0.057)	(0.053)	(0.091)	(0.175)	(0.090)	(0.087)
Age^2	0.001**	0.000	0.000	0.002**	0.001*	0.001	0.001	0.003**	0.002*	0.000	0.002**	0.004**	0.001	-0.001	0.001	0.002**
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Average age of hh	0.029**	0.022*	0.032**	0.047**	0.008	-0.003	0.002	0.010	0.011	0.017	0.021	0.024*	0.062	-0.083	0.045	0.054
	(0.008)	(0.011)	(0.008)	(0.008)	(0.013)	(0.023)	(0.013)	(0.013)	(0.014)	(0.017)	(0.012)	(0.012)	(0.035)	(0.086)	(0.035)	(0.035)
average # in hh w/no ed	-0.728*	-0.934	-0.729*	-0.984**	-0.020	20.151**	0.176	-0.279	-1.077	-1.635	-1.222*	-0.845	-0.724	2.160	-0.366	-0.260
	(0.369)	(0.531)	(0.369)	(0.381)	(0.706)	(1.902)	(0.704)	(0.749)	(0.562)	(1.010)	(0.512)	(0.480)	(0.787)	(1.177)	(0.739)	(0.687)
average # in hh w/pr ed	-0.770*	-0.647	-0.664	-1.215**	-0.187	19.875**	-0.070	-0.693	-0.677	-0.224	-0.767	-0.434	0.038	4.112**	0.266	0.085
	(0.344)	(0.427)	(0.350)	(0.345)	(0.714)	(1.881)	(0.718)	(0.751)	(0.458)	(0.758)	(0.418)	(0.401)	(0.900)	(1.556)	(0.863)	(0.829)
average # in hh w/sec ed	-1.077**	-0.689	-0.895*	-1.533**	-0.392	20.655**	-0.321	-0.690	-0.689	-1.156	-1.072*	-0.831	0.355	3.507*	0.752	0.234
	(0.368)	(0.421)	(0.383)	(0.367)	(0.717)	(1.930)	(0.724)	(0.790)	(0.471)	(0.788)	(0.446)	(0.431)	(1.328)	(1.748)	(1.296)	(1.289)
average # in hh w/ter ed	-1.971**	-1.151	-0.013	-0.875	-1.308	19.621**	0.127	0.303	-0.020	-0.616	-0.413	-0.054	33.550	-105.202	-65.199	-33.196
	(0.609)	(0.654)	(0.567)	(0.490)	(1.456)	(2.229)	(1.295)	(1.117)	(0.679)	(0.812)	(0.675)	(0.602)	(20667255)	(809517922)	(49197247)	(14706146)
Number of children in hh	0.106*	-0.142*	0.009	-0.037	0.080	0.140	0.078	0.100*	0.023	-0.135	0.081	0.098	0.188	-0.716	0.231	0.265
	(0.044)	(0.064)	(0.042)	(0.044)	(0.048)	(0.091)	(0.048)	(0.049)	(0.081)	(0.124)	(0.079)	(0.075)	(0.234)	(0.590)	(0.230)	(0.221)
Number of teens in hh	0.196**	-0.105	0.053	0.232**	-0.216*	-0.089	-0.205*	0.002	-0.032	0.140	0.028	-0.024	-0.128	-1.065	-0.090	-0.054
	(0.063)	(0.096)	(0.067)	(0.067)	(0.086)	(0.160)	(0.087)	(0.090)	(0.107)	(0.170)	(0.106)	(0.093)	(0.224)	(0.702)	(0.220)	(0.211)
Number of adults in hh	0.009	0.064	-0.048	0.002	0.032	0.265	0.077	0.122	0.001	-0.072	-0.068	-0.011	0.213	4.114	0.423	0.400
	(0.056)	(0.081)	(0.062)	(0.058)	(0.095)	(0.173)	(0.106)	(0.096)	(0.087)	(0.172)	(0.086)	(0.080)	(0.815)	(2.274)	(0.812)	(0.717)
Number of elderly in hh	-0.137	-0.075	-0.252	-0.468**	-0.126	0.512	0.115	-0.159	-0.175	-0.063	-0.116	-0.147	-0.560	0.807	-0.326	-0.291
	(0.174)	(0.309)	(0.184)	(0.181)	(0.288)	(0.444)	(0.301)	(0.296)	(0.274)	(0.440)	(0.273)	(0.246)	(0.851)	(1.081)	(0.855)	(0.814)
Household head	0.106	0.457	0.817**	-1.157**	-0.416	1.226	0.494	-1.522**	-0.957	-0.415	0.415	-0.363	1.133	0.767	2.131	0.980
	(0.263)	(0.469)	(0.291)	(0.272)	(0.365)	(0.861)	(0.427)	(0.377)	(0.529)	(0.620)	(0.490)	(0.483)	(1.932)	(2.129)	(1.909)	(1.861)
Spouse	0.583	0.950	0.826	-0.254	20.126**	23.868	21.819**	19.548**	-0.129	-0.054	1.577**	1.497**	0.224	0.348	1.713	1.593
	(0.768)	(1.043)	(0.786)	(1.013)	(1.040)	(.)	(0.995)	(1.081)	(0.313)	(0.464)	(0.329)	(0.285)	(0.893)	(1.032)	(0.907)	(0.858)
Guatemala City	1.630**	2.073**	1.561**	1.510**	1.553	-31.779**	2.138*	1.261	0.373	0.424	0.823*	0.775*	0.989	-5.106	2.090*	2.392**
	(0.317)	(0.424)	(0.329)	(0.335)	(0.935)	(1.815)	(0.969)	(1.053)	(0.363)	(0.574)	(0.355)	(0.337)	(1.131)	(4.206)	(0.902)	(0.728)
Rural	0.349*	0.304	0.841**	0.460**	0.395	-0.074	0.474*	0.826**	0.304	0.043	0.949**	1.465**	0.685	2.215**	1.221*	1.346*
	(0.156)	(0.335)	(0.163)	(0.171)	(0.222)	(0.418)	(0.228)	(0.240)	(0.260)	(0.511)	(0.250)	(0.229)	(0.596)	(0.831)	(0.585)	(0.566)
Constant	1.785**	-3.362**	-2.424**	2.535**	3.633**	-24.132	0.550	4.426**	3.980**	-2.930	1.912	6.417**	1.424	-13.325*	-1.333	2.427
	(0.569)	(1.104)	(0.613)	(0.616)	(0.945)	(.)	(0.958)	(0.985)	(1.018)	(1.938)	(0.982)	(0.937)	(2.763)	(6.475)	(2.674)	(2.553)

Standard errors in parentheses; ** significant at 99% level; * significant at 95% level

Table A-3 (continued)

(iv) Guyana

Educational Multinomial

	Indo Men		(N=1232)	***Afro Men***		(N=1116)	***Indo Women***		(N=1265)	***Afro Women***		(N=1308)
Variable	Primary	Secondary	Tertiary	Primary	Secondary	Tertiary	Primary	Secondary	Tertiary	Primary	Secondary	Tertiary
Age	0.006	-0.008	0.142	-0.020	0.059	0.192**	-0.007	-0.048	0.271	0.044	0.070	0.235**
	(0.030)	(0.039)	(0.080)	(0.047)	(0.051)	(0.063)	(0.029)	(0.043)	(0.151)	(0.034)	(0.040)	(0.056)
Age^2	-0.000	-0.001	-0.002*	0.000	-0.001	-0.002**	-0.000	-0.001	-0.003	-0.001	-0.001**	-0.003**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.002)	(0.000)	(0.000)	(0.001)
Georgetown	0.094	0.610	-0.178	0.926	0.938	1.089	0.349	0.736	1.588	0.415	0.625	1.251*
	(0.591)	(0.628)	(0.732)	(0.687)	(0.686)	(0.732)	(0.445)	(0.517)	(1.159)	(0.492)	(0.496)	(0.578)
Rural	-0.619	-1.084*	-2.274**	-0.246	-1.345**	-1.418*	-0.258	-0.437	-0.678	-0.536	-1.267**	-0.397
	(0.483)	(0.522)	(0.619)	(0.496)	(0.501)	(0.570)	(0.346)	(0.418)	(1.117)	(0.403)	(0.411)	(0.510)
Constant	2.546**	2.400**	-1.691	3.035**	2.250*	-2.822*	2.789**	3.271**	-7.470*	1.879*	2.261**	-3.627**
	(0.790)	(0.918)	(1.647)	(1.019)	(1.072)	(1.364)	(0.708)	(0.901)	(3.447)	(0.802)	(0.867)	(1.196)

Demographic Multinomial

	Indo Women		(N=927)			***Afro Women***		(N=815)		
Variable	1 children	2 children	3 children	4 children	> 4 children	1 children	2 children	3 children	4 children	> 4 children
Age	-0.112**	-0.190**	-0.250**	0.260	-0.034	0.043	0.042	0.142*	0.055	0.195
	(0.039)	(0.045)	(0.052)	(0.203)	(0.262)	(0.042)	(0.050)	(0.069)	(0.072)	(0.144)
Age^2	0.001	0.001*	0.002**	-0.005	-0.001	-0.001	-0.001*	-0.003**	-0.001	-0.003
	(0.000)	(0.001)	(0.001)	(0.003)	(0.004)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)
Primary	-0.453	-0.555*	-0.613	-0.404	-0.815	-0.364	-1.742**	-1.390*	-1.728*	-1.819*
	(0.252)	(0.278)	(0.351)	(0.582)	(0.824)	(0.626)	(0.596)	(0.680)	(0.705)	(0.830)
Secondary	-0.283	-0.518	-0.482	-0.560	-32.077	-0.554	-1.923**	-1.953**	-2.259**	-3.300**
	(0.337)	(0.358)	(0.449)	(0.726)	(4344017)	(0.652)	(0.622)	(0.707)	(0.753)	(0.963)
University	-0.078	-0.558	-31.104	-31.099	-31.464	-0.278	-1.955**	-2.643**	-38.123	-38.432
	(0.723)	(0.906)	(5303136)	(8367188)	(15581502)	(0.685)	(0.674)	(0.837)	(29.564)	(41.077)
Georgetown	0.111	0.300	-0.585	-0.861	-0.440	-0.447	-0.536	-1.019**	-1.303**	-0.162
	(0.411)	(0.450)	(0.620)	(0.830)	(1.456)	(0.285)	(0.303)	(0.343)	(0.500)	(0.871)
Rural	-0.113	-0.028	-0.193	-0.667	-0.515	-0.186	-0.433	-0.528	-0.145	0.807
	(0.347)	(0.385)	(0.473)	(0.602)	(1.101)	(0.282)	(0.304)	(0.327)	(0.416)	(0.787)
Constant	3.294**	5.585**	6.187**	-3.227	1.310	0.333	2.255*	0.312	1.091	-2.230
	(0.964)	(1.039)	(1.205)	(3.569)	(4.577)	(1.075)	(1.121)	(1.449)	(1.555)	(2.737)

Occupational Multinomial

	Indo Men		(N=1144)	***Afro Men***		(N=1026)	***Indo Women***		(N=1198)	***Afro Women***		(N=1229)
Variable	Unemployed	Self-empl	Employee	Unemployed	Self-empl	Employee	Unemployed	Self-empl	Employee	Unemployed	Self-empl	Employee
Primary	1.799	0.555	0.320	18.290**	0.733	0.751	0.155	0.147	-0.475	0.105	-0.162	0.752
	(1.120)	(0.351)	(0.299)	(1.480)	(0.573)	(0.455)	(0.698)	(0.309)	(0.322)	(0.790)	(0.563)	(0.527)
Secondary	0.836	0.565	0.076	18.586**	0.630	0.895	0.837	0.030	0.634	0.580	0.139	1.245*
	(1.271)	(0.416)	(0.354)	(1.487)	(0.611)	(0.482)	(0.787)	(0.450)	(0.368)	(0.797)	(0.586)	(0.535)
University	2.498	0.867	0.832	18.639**	0.109	1.643**	-31.513	-33.929	1.450*	0.584	-1.005	2.141**
	(1.634)	(0.730)	(0.629)	(1.773)	(0.785)	(0.594)	(36282908)	(20552719)	(0.732)	(1.008)	(0.792)	(0.580)
Age	0.004	0.345**	0.229**	0.265**	0.318**	0.331**	0.001	0.292**	0.213**	0.124	0.316**	0.272**
	(0.103)	(0.053)	(0.040)	(0.082)	(0.048)	(0.039)	(0.103)	(0.055)	(0.050)	(0.066)	(0.059)	(0.035)
Age^2	-0.001	-0.004**	-0.003**	-0.003**	-0.004**	-0.004**	-0.001	-0.003**	-0.003**	-0.002*	-0.004**	-0.003**
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Average age of hh	-0.013	-0.025	-0.033**	-0.023	-0.004	0.011	0.019	-0.029*	-0.008	-0.014	-0.015	-0.007
	(0.028)	(0.013)	(0.011)	(0.025)	(0.014)	(0.011)	(0.025)	(0.013)	(0.013)	(0.018)	(0.013)	(0.009)
average # in hh w/no ed	1.638	2.080*	3.089**	-228.203	-0.134	-0.172	-0.243	1.066	0.096	-2.252	0.876	0.805
	(1.597)	(0.820)	(0.753)	(14656729)	(0.880)	(0.710)	(1.404)	(0.690)	(0.721)	(1.596)	(0.930)	(0.645)
average # in hh w/pr ed	0.174	1.236	2.571**	-0.003	0.619	0.083	-0.580	0.118	-0.038	-1.002	0.747	0.015
	(1.421)	(0.700)	(0.651)	(1.099)	(0.638)	(0.537)	(1.263)	(0.618)	(0.612)	(0.817)	(0.574)	(0.441)
average # in hh w/sec ed	-2.434	1.611*	2.477**	-0.608	0.655	0.146	-1.197	-0.611	-0.881	-1.411	0.223	0.352
	(2.033)	(0.719)	(0.667)	(1.050)	(0.625)	(0.518)	(1.284)	(0.638)	(0.613)	(0.781)	(0.551)	(0.410)
average # in hh w/ter ed	2.787	0.410	2.336*	-0.817	0.310	-0.253	-109.375	1.087	0.754	-2.499*	0.659	0.204
	(2.159)	(1.393)	(1.092)	(1.495)	(0.888)	(0.694)	(16379087)	(0.923)	(0.793)	(1.247)	(0.758)	(0.514)
Number of children in hh	-0.118	0.125	0.103	0.342**	0.185*	0.129	0.271	-0.107	-0.114	0.070	-0.003	-0.088
	(0.229)	(0.093)	(0.083)	(0.122)	(0.083)	(0.068)	(0.139)	(0.097)	(0.085)	(0.089)	(0.073)	(0.053)
Number of teens in hh	-0.318	-0.234	-0.125	0.138	-0.171	-0.007	0.173	0.238	0.060	-0.006	0.035	0.085
	(0.297)	(0.125)	(0.102)	(0.168)	(0.129)	(0.095)	(0.207)	(0.124)	(0.111)	(0.141)	(0.115)	(0.079)
Number of adults in hh	0.096	-0.014	-0.098	-0.048	-0.108	-0.079	-0.127	-0.100	-0.174	0.204	-0.142	-0.052
	(0.234)	(0.102)	(0.083)	(0.145)	(0.098)	(0.067)	(0.207)	(0.113)	(0.097)	(0.107)	(0.114)	(0.066)
Number of elderly in hh	0.779	0.363	0.194	0.675	0.371	-0.085	-0.750	0.419	-0.544	0.390	-0.729	0.104
	(0.527)	(0.290)	(0.234)	(0.543)	(0.305)	(0.252)	(0.775)	(0.321)	(0.365)	(0.446)	(0.494)	(0.234)
Household head	1.429	2.299**	1.440**	-1.039	1.898**	1.257**	1.336	0.509	0.018	-0.394	1.709**	0.147
	(0.882)	(0.407)	(0.331)	(0.677)	(0.404)	(0.320)	(0.894)	(0.455)	(0.429)	(0.569)	(0.450)	(0.273)
Spouse	0.839	1.066	-0.124	-33.298	0.131	0.340	-0.437	-0.708	-1.480**	-0.778	0.129	-1.534**
	(1.267)	(0.596)	(0.531)	(9012395)	(0.624)	(0.455)	(0.696)	(0.373)	(0.322)	(0.452)	(0.420)	(0.240)
Georgetown	19.907**	-0.585	-0.003	-0.598	0.386	0.417	-0.394	-0.033	0.852*	-0.467	-0.139	0.250
	(2.307)	(0.501)	(0.419)	(0.420)	(0.346)	(0.265)	(0.854)	(0.465)	(0.399)	(0.339)	(0.289)	(0.213)
Rural	19.048**	0.115	0.048	-1.710**	0.908**	0.827**	-0.419	-0.533	-0.384	-1.006**	-0.323	0.098
	(2.252)	(0.418)	(0.365)	(0.508)	(0.329)	(0.257)	(0.644)	(0.384)	(0.361)	(0.362)	(0.288)	(0.215)
Constant	-22.368	-7.989**	-4.445**	-22.831	-8.394**	-6.935**	-2.566	-6.328**	-3.153**	-2.702*	-7.757**	-5.945**
	(.)	(1.157)	(0.926)	(.)	(1.113)	(0.874)	(1.928)	(1.165)	(0.999)	(1.358)	(1.226)	(0.841)

Standard errors in parentheses; ** significant at 99% level; * significant at 95% level