Implications for public policies from changes in age-education composition

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The topic addressed here is related to, but different in its focus from recent studies of the "demographic dividend" whereby the changing age structure in developing countries resulting from sustained and rapid fertility decline presents a temporary "window of opportunity" during which a reduced dependency ratio yields high rates of growth in income per capita. This positive impact on growth derives from the mechanical link between the size of the working age and total population, increases in labor supply due to higher proportions of women becoming employed, higher savings rates, higher rates of human capital formation, and, possibly, from the impact of population aging on capital accumulation via capital deepening. That the decline in the dependency ratio, caused by rapid fertility decline, has substantially influenced economic development in East and Southeast Asia has been shown often (e.g., Bloom and Freeman 1986; Bloom *et al* 2003; Williamson 2003; Mason 2005; Mason and Feng 2005). These authors stress the transitory nature of the decrease in the dependency ratio, and as well conditional nature of the dividend: the drop in the dependency ratio will only result in economic growth in the right policy environment.

While the demographic dividend literature focuses on the ratio of the population of working age to the rest of the population, the analysis engaged in this study focuses on the changes in age structure within the population of working age that necessarily accompany the demographic transition, as well as the concurrent change in levels of education that normally accompanies and may even drive the demographic transition. Whereas in the dividend literature, the focus is mainly on aggregated outcomes, the concern is with the distribution of economic outcomes within the labor force and how these may be affected by its changing composition.

Evidence from studies of the U.S. baby boom has suggested that increases in factor supplies led to the decline in wage rates of the expanding sub-aggregates, confirming the role of negative own-quantity elasticities of factor price. Similarly, one would expect that an increase in the supply of skilled labor will lead to a relative decline in its wage rate. In developed countries, however, this decline has not been observed, with the skill premium increasing along with the supply of educated workers (Katz and Murphy 1992; Autor *et al* 1998). The reasons may be skill-biased technical change, the role of international trade, or other factors; but the results require expanding the usual production-function framework.

Despite their difficulties in describing aggregate trends over the past three decades, studies of labor-labor substitution in rich countries illustrate the power of a formal factor-demand framework. These studies also take advantage of the richness of combining age (experience) and schooling as basic labor inputs, thus driving variations in wage rates. While the technology-constant microeconomic findings are swamped at the macro level by trends arising from aggregate shocks, they support the basic tenets of production theory. Using data at the micro level from a developing country makes it possible to take a formal model and estimate more precisely how changing cohort size and skill alter relative wage differentials.

Influence of age, experience and cohort size on earnings

The first demographic dividend is determined by the direct impact of the age structure (ratio of working-age population to total population) on per-capita income. The decline in the dependency ratio had positive impacts on the economic development of Asian countries that experienced rapid fertility decline. Since this literature is based on the influence of age and education compositions on economic outcomes, it is essential to highlight the contributions made by Mincer (1974) on the connections involving schooling, experience, and earnings.

One of Mincer's objectives was to estimate the relation between accumulated investments in human capital of workers and their earnings. Moreover, the earnings function was used to determine how the individual differences of investments in human capital can influence inequality in the distribution of labor incomes. Finally, earnings functions helped the understanding of whether earnings structure can be comprehended in terms of human capital investment behavior.

Mincer was concerned about the estimation of earnings functions because previous studies solely utilized the linear impact of years of schooling on log earnings. The observed correlation between education and earnings was not strong in those models, because variations in earnings associated with age were not captured:

> Though age can be viewed as an inherent depreciation phenomenon in the human capital terminology, the growth of earnings with age can ultimately be interpreted in the human capital model as being a consequence of net self-investment activities that are continued after the completion of schooling. The theory predicts that investments are concentrated at younger ages, but continue at a diminishing rate throughout much of the working life; because of increasing marginal costs, investments are not made all at once in a short period, but are staggered over time, and decline continuously, both because benefits decline as the payoff period shortens, and because opportunity costs are likely to rise with experience (Mincer 1974, p. 129).

Hence, to expand the schooling model into a more complete earnings function, the linear schooling term must be improved by the use of a nonlinear years-of-experience term:

> This function can be applied in multiple regression analysis to earnings data of individuals who differ in both schooling and age. While age is not the same as work experience, the latter can be estimated as actual age minus estimated age at completion of schooling, though direct information on experience is preferable. Clearly, direct information on experience is necessary for specifying earnings functions of individuals whose attachment to the labor force is not continuous (Mincer 1974, p. 129).

The use of experience is most appropriate on studies of female earnings. Studies on male earnings would not be biased if age is used instead of experience, because this group is continuously attached to the labor force. The use of both years of schooling and experience as independent variables in earnings functions improve the results, with even better results when weeks worked during the year is included as an explanatory variable.

The choice of expressing earnings in dollars or in logs depends on how information concerning schooling and experience are expressed:

> If dollar values are used, the investment variables (schooling and experience) must also be expressed in dollars. If log earnings are used, then the investment variables can be expressed in units of time — years of schooling and years of experience. The time measures of investment are far more readily available than the dollar ones. For both reasons then — interest in relative comparisons and data availability — the logarithmic formulation is preferred (Mincer 1974, p. 130).

Further studies indicate that not only the independent impact of age and education explain earnings, but also cohort size. In other words, the productivity factor (ratio of total income to employment) can be affected by a shift in the population's age structure, generating a second demographic dividend. The productivity component can be exogenously influenced by shifts in the age and educational structures, according to the shape of the labor demand curve for each age and educational labor factor. Studies about influences of changes in age structure on earnings usually focus only on the male labor force trends, partly because these exogenous changes in age structure (fertility decline) and in educational attainment are significantly associated to female labor force participation.

The significance of fertility swings and shifting age distribution on economic development was analyzed in studies of the influence of the "baby boom" on labor market outcomes in the United States (Easterlin 1978; Freeman 1979; Welch 1979). Cohorts born during the "baby boom" entered the American labor market between the end of the 1960s and the middle of the 1970s. The new labor force entrants had more schooling than earlier cohorts: (1) the number of persons with 5–8 years of schooling and with 1–3 years of high school fell considerably; (2) the number of high school graduates, and those with at least some college increased significantly.

Easterlin (1978) suggests that the increase in the ratio of younger to older adults after the 1940s in the United States had pervasive socioeconomic implications. Because of this increase, the relative economic position of young adults fell after the 1960s when they entered the labor market. The Easterlin hypothesis implies that these changes in birth rates and cohort size influence trends in demographic and social behavior. More than reducing the economic opportunities of the large cohorts of young adults, this phenomenon results in the decline of fertility rates, the postponement of marriage, higher divorce rates, higher levels of female labor force participation, increasing homicide, suicide and political alienation. As a consequence of a cycle process, the smaller cohorts introduced to the labor market in the 1990s will experience higher relative earnings than other groups, as well as more traditional family structures.

Pampel and Peters (1995) review several studies that tested the Easterlin hypothesis. They examine literature from diverse academic disciplines that offer evidence to support or contradict the different socioeconomic consequences of changing cohort size as suggested by Easterlin. Studies on European countries are also analyzed in order to provide comparative evidence to the U.S. findings, helping to identify the strengths and weaknesses of the theory. Because shifts in gender roles and values may have happened across time and may have changed the application of the theory on recent experiences in comparison to past decades, Pampel and Peters review studies with different temporal scopes. Finally, studies that used different methods are reviewed by the authors, in order to determine whether Easterlin's theory might have a better use in aggregate data or in individual-level studies. The main findings suggest that:

> (...) aggregate data support the hypothesis more than individual-level data, period-specific or time-series data support the hypothesis more than cohort-specific data, experiences from 1945–1980 support the hypothesis more than the years since 1980, and trends in the United States support the hypothesis more than trends in European nations. Given these data qualifications, the predictions of the Easterlin effect best fit aggregate, period trends from 1945–1980 in the United States. The conceptual broadness of the phenomena potentially explained by the theory represents a strength, but the empirical evidence does not extend as far as the theory suggests (Pampel and Peters 1995, p.189).

As elucidated by Macunovich (1998), the extensive literature on fertility aspects of the Easterlin hypothesis gives support to the theory, but the relationship has been changing across countries and time periods. Macunovich observes that because of data limitations and individual interpretations of the hypothesis, many studies with opposite findings have been weakly related to the Easterlin hypothesis. Simplified interpretations of the hypothesis resulted in a tendency to abandon this theory. These inquiries centered the analysis around the relationship between relative cohort size and fertility, instead of on the relationship between relative income and fertility. Moreover, these interpretations of the Easterlin hypothesis only dealt with the factor of cohort size and did not include other elements that could have an effect on income and fertility trends. Summarizing her analysis, Macunovich indicates that:

> In *aggregate analyses*, studies which find little or no support for the Easterlin hypothesis tend to be those which: [1] use variables which are not *age-specific* (This is particularly true of the

European analyses: *none of the aggregate studies of countries outside North America have used age-specific relative income measures*); [2] use relative cohort size or relative income variables without any other controls; [3] attempt to fit the Easterlin model with older (age 30+) age groups; [4] treat family income and male earnings as interchangeable; [5] use relative cohort size rather than relative income as the independent variable (especially in later years). In *microlevel analysis*, studies which find little or no support for the Easterlin hypothesis tend to be those which: [1] treat family income and male earnings as interchangeable; [2] use only the husband's characteristics in formulating relative income variables, without information on his or his wife's parents; [3] focus the analysis only on women in intact first marriages with no 'unwanted' or 'unintended' births, and analyze fertility with age at marriage held constant; [4] with categorical rather than continuous measures of relative income, treat the second generation's minimum consumption threshold (i.e. the level of affluence required before they feel able to support a family) as *equal* to first generation income, rather than a *function of* it; [5] use expected or desired rather than actual fertility (Macunovich 1998, p.98).

Supportive analyses of the Easterlin hypothesis validate further work in this area. Freeman (1979) studied the effect of changes within the age structure of the workforce on age-earnings profiles in the United States. Because of the "baby boom" that followed World War II and peaked between 1955–1960, there was an especially significant change in the age structure of the U.S. workforce in the late 1960s and early 1970s. This timeframe was a period when the number of young persons increased very rapidly. The key finding was that the age-earnings profile of male workers appears to be significantly influenced by the age composition of the workforce. In prior studies, the age-earnings profile was usually viewed as a stable economic relationship determined by human capital investment decisions, assuming that earnings only rise with age and experience as a result of individual investment behavior. Freeman notes that from the late 1960s through the mid-1970s, when the number of young workers increased rapidly, the earnings of young male workers fell relative to the earnings of older male workers, altering male age-earnings profiles, particularly for college graduates.

Welch (1979) scrutinized the 1968-1976 March Current Population Surveys (CPS) in order to assess the impact of the change in age composition experienced by the United States. due to the entrance of the post-World War II baby boom cohorts into the job market. The main hypothesis was again that the changing age composition of the workforce affected earnings patterns. The key finding was that the pressure of a workforce whose average age is rapidly declining results in the reduction of the wages of new entrants. Welch points out that there is strong evidence that large cohorts do depress earnings, and that these effects increase with level of schooling. Moreover, most of the negative effect on earnings comes early in the individual's career, suggesting that negative effects rapidly diminish and reach a smaller permanent level at a relatively young age.

Berger (1985) suggests that the negative effects of cohort size on earnings do not diminish rapidly, contrary to what Welch observes. Cohort size also has a negative effect on early career earnings growth, which is in opposition to Welch's findings. The impact of cohort size on earnings may actually increase throughout the careers of individuals in large cohorts. These trends are explained by Berger, as follows:

> (...) using data almost identical to those employed by Welch, the restrictions inherent in his empirical model are rejected in favor of a more general model, which involves separate earnings equations for older and younger worker subsamples. (...) Cohort size effects on earnings levels appear to widen with experience, suggesting a continually increasing cohort size earnings 'penalty' as workers in large cohorts move through their careers. This suggests that there will be no quick recovery of the earnings levels of workers in large entry cohorts as is implied by Welch's study. At the very least, the lower observed rates of earnings growth in large cohorts are consistent with slower speeds of transition between the learning and fully trained stages of the career (Berger 1985, p.572).

These cohort-size studies suggested that shifts in factor supply (the baby boom) led to a decline in wages, so that demand shifts did not explain all the wage variation. By the same token, an increase in the supply of skilled labor should lead to a relative decline in the wage of skilled relative to unskilled labor. In the context of a production function with a constant elasticity of substitution (CES) and downward-sloping demand for relative skill, an increase in the provision of skilled labor will lead to a decline in the skill premium (defined as the wage of skilled workers divided by that of unskilled). In developed countries, in contrast, the skill premium increased while the supply of educated workers has risen steadily. Katz and Murphy (1992) found that the relative supply of skilled labor combined with smoothly rising demand explains U.S. relative wage trends between 1967 and 1987. Autor *et al* (1998) used a longer time series to test the smooth rising demand hypothesis, and found some evidence that accelerating demand rationalized the U.S. wage premium shifts. An alternative justification for the rising wage premium is the role of trade, the U.S. engagement with countries in which skills are relatively scarce. An institutional explanation may also be suggested to the extent that the real minimum wage and the bargaining power of unions declined during this period.

Triest *et al* (2006) have conducted the most recent analysis of population aging and the structure of wages in the United States. Their research explores the effect of labor market experience, relative cohort size and real wage growth on real wages by level of education using the March Current Population Survey (CPS) from 1964 and 2004. Referring to the Census Bureau, the authors emphasize that the working population in the United States will increase by 13 percent between 2001 and 2025, but the population between 60 and 64 years of age will increase by 90 percent. This process shows that the cohorts of baby boomers are entering retirement ages, increasing the elderly dependency ratio, as well as decreasing the growth rate of the working age population. This demographic dynamic will have some influence on economics: "as a consequence, labor supply may grow at a slower rate than labor demand, putting upward pressure on wages and creating tight labor market conditions. Often overlooked, however, is the fact that the age distribution of the labor force will also be changing." (Triest *et al* 2006, p.1)

Triest *et al*'s models indicate that: (1) increases in relative cohort size are associated with decreases in wages; (2) although real wages initially increase with labor market experience, there is a significant decrease in the rate of growth as experience increases; (3) there was a general increase in the economic return to educational attainment; (4) changes in the age and experience composition of the labor force will continue to have an important influence on the structure of wages; (5) the initial increase in the experience premium generated by the baby boom's entry into the labor market is now being reversed as the baby boom progresses through middle age and approaches retirement. More specifically, the authors stress that baby boomers born in 1950 encompassed a large fraction of the college educated labor force when they entered the labor market. At that time, their wages would have been 18 percent higher if their relative cohort size was the same as that of the 1970 cohort when entering the labor force. Large cohorts depress their own wages relative to those of other cohorts in the labor force at the same time. Triest *et al* imply that changes in the age and experience composition of the labor force will continue to have an important influence on the structure of wages.

While these studies all refer to the U.S. case, they illustrate the power of the supply-demand framework and the richness of combining age and schooling as basic labor inputs, thus driving wage variations.

Brazilian microdata

The shocks that generated subsequent changes in relative labor supply by cohort began some decades ago in Brazil, with data suggesting that fertility decline initiated in the 1940s in Porto Alegre, São Paulo, and Rio de Janeiro. In the early 1960s, the decline in fertility in the metropolitan areas of Rio de Janeiro, São Paulo, and Porto Alegre led to total fertility rates below five. From these locations the decline spread to the interior of these Southeastern states, and to the capital cities of states in the Central-West, North and Northeast, finally reaching the interior and rural areas of those regions in the 1980s. At the municipal level in 2000 there were a substantial number of entities with total fertility rates above four, while there were also many where fertility had fallen below replacement. The variation in the timing and speed of the fertility transition led to substantial differences in the age distribution across states and municipalities, as well as across different points in time (Potter *et al* 2002).

The longest series of data on age, education and earnings come from the Brazilian Censuses conducted in 1960, 1970, 1980, 1991, and 2000. Microdata from these Censuses are available from long-form questionnaires administered to 25-percent samples in 1960, 1970, and 1980. In 1991 and 2000 the sample sizes depended on the size of the municipality, with 10-percent samples from municipalities with more than 15,000 inhabitants, and 20-percent samples from all other municipalities. In all cases there are records for every individual in the sampled households, containing information on age, gender, marital status, educational attainment, enrollment in school, and, if employed, occupation and earnings. There are also questions on migration, including state of birth, previous residence, and residence five years before the Census.

The lowest level of geographic identifier on these records common to all Censuses is the *município*, since information on *distritos*, the sub-divisions of *municípios*, is not available in the Census microdata. In a previous work, Potter *et al* (2002) established minimum comparable areas that account for the changing definitions and divisions of *municípios* across the Census years, which is necessary since their number increased from approximately 2,300 in 1960 to 5,280 in 2000. The authors were able to aggregate minimum comparable areas into 502 micro-regions across the five Censuses. It is important to note that these micro-regions differ from those defined by the Brazilian Institute of Geography and Statistics (IBGE) and those available in the Census microdata, but closely approximate those defined for the 1991 Census. It is thus possible to calculate various statistics summarizing the age distribution, labor-market outcomes and education indicators for each of these 502 consistently defined areas in each of the five Censuses. In the end, because the 1960 Census categorized earnings by bracket, this Census is excluded and the analyses are based on the Censuses beginning in 1970.

Since there is a very pronounced trend in the age distribution that has substantial variation across regions, states and municipalities, this study seeks to take advantage of this change at the micro-region level. Using these very small geographical units poses the question of internal migration, which has not been incorporated in most preceding analyses conducted at the national level. The migration component could be an important factor in this context, since the main population streams have been moving from areas with higher fertility to those with lower fertility. While such migration tends to lessen the differential in fertility between sending and receiving areas, the greater likelihood that migrants will be of working age actually increases the variation in dependency rates. Borjas *et al* (1997) develop a discussion of the role of internal migration on modifying the impacts of exogenous changes in relative supply on relative wage rates. This potential problem will be discussed in more detail later.

Summary of models

The general conclusion from the findings elaborated by Amaral *et al* (2007) is that the impact of distribution of male population in age-education groups on earnings is changing over time, with a decrease in the negative elasticities for the least-educated groups, indicating that the small proportional size of these groups do not have a significant impact on earnings in more recent years. For better educated groups, the negative impact has been increasing over time with slight variations in more recent years. Table 1 illustrates the F-statistics that test whether all coefficients are equal to zero, and whether the area fixed effects are equal to zero for the models elaborated by Amaral *et al* (2007). The fraction of the variance due to the area fixed effects (v_i) — Rho — is included in the table.

The maximum number of possible observations in the regression is 24,096, because there are 502 micro-regions, 12 age-education groups and four Censuses. Because of the requirement that the cells should have at least 25 men receiving earnings, there were 19,727 observations throughout the models. In general, the statistics in Table 1 indicate that for models with fewer variables, and consequently with fewer coefficients to be estimated, the F-statistics are larger. All models presented significant estimates, suggesting that the null hypothesis is not true. For the model with the highest amount of independent variables (2,630), including cross-proportions interacted with year and five major-region indicators; the fraction of variance due to the area fixed effects was 0.98.

Table 1. Summary of F-Statistics from the Model Only With Age-Education-Group and Year Indicators, from Equations (1), (1'), (2), (2'), and from Models Including Interactions With Micro-region Size and Region Indicators.

Models	**All Coefficients=0**	**Area Fixed Effects=0 (F-Test that All υ_i=0)**	**Rho: Fraction of Variance Due to the υ_i**
Model only with year and age-education indicators	F (14; 19,211): 12,941.99***	F (501; 19,211): 65.13***	0.66
Equation (1): Own-effects	F (26; 19,199): 8,506.08***	F (501; 19,199): 57.02***	0.73
Equation (1'): Own-effects X Year	F (62; 19,163): 3,957.16***	F (501; 19,163): 53.20***	0.74
Equation (2): Cross-effects	F (146; 19,079): 1,808.52***	F (501; 19,079): 20.82***	0.68
Equation (2'): Cross-effects X Year	F(542; 18,683): 538.51***	F(501; 18,683): 20.87***	0.66
Equation (1) X Region indicators	F(74; 19,151): 3,169.42***	F(501; 19,151): 27.40***	0.69
Equation (1') X Region indicators	F(266; 18,959): 1,023.04***	F(501; 18,959): 25.76***	0.68
Equation (2) X Region indicators	F(674; 18,551): 423.38***	F(501; 18,551): 13.65***	0.89
Equation (2') X Region indicators	F(2,630; 16,595): 125.77***	F(501; 16,595): 12.19***	0.98
Equation (1) X Micro-region size	F(65; 19,160): 3,510.03***	F(501; 19,160): 55.16***	0.73
Equation (1') X Micro-region size	F(214; 19,011): 1,172.15***	F(501; 19,011): 50.75***	0.73
Equation (2) X Micro-region size	F(545; 18,680): 504.12***	F(501; 18,680): 20.53***	0.71
Equation (2') X Micro-region size	F(2,040; 17,185): 150.08***	F(501; 17,185): 19.26***	0.68

* Significant at p<.05; ** Significant at p<.01; *** Significant at p<.001.
Source: 1970–2000 Brazilian Censuses.

Decomposition of age and education impacts on earnings

Some consideration should be given to the implications for public policies originating from the analysis by Amaral *et al* (2007). The decomposition of the impact of changes in age-education groups on earnings provides insight about the separated impact of age and education changes.

One can hold constant the age structure from the 1970 Census, and use the education structure from the 2000 Census to estimate earnings in 2000. Comparing these new estimated earnings to the original 2000 predicted earnings (using age and education structures from 2000) measures the effect of changing age composition on earnings. For example, if age structure had remained the same from 1970 to 2000, one can compare these new results to the 2000 original predicted values to verify that groups who experienced proportional increases over time (age-groups 25–34, 35–49, and 50–64) had smaller original earnings in 2000, compared to the earnings with constant age structure. In the opposite case, earnings in 2000 can be predicted utilizing the 1970 education structure and the 2000 age structure. These new estimated earnings can be compared to the 2000 original predicted earnings to analyze the impact of changing education composition on earnings.

First of all, national proportions of males by age-education group and Census year were used to generate two new sets of national proportions: (1) holding age composition constant from 1970; and (2) holding education composition constant from 1970. In an additional step, these two new standardized compositions were used to forecast four sets of earnings: (1) two sets of earnings were generated applying the coefficients from the own-effects model (Equation (1)) and are shown in Table 2; and (2) two sets of earnings were estimated using the coefficients from the own-effects model interacted with year indicators (Equation (1’)) and are illustrated in Table 3.

Thus, Tables 2 and 3 show: (1) the 1970 predicted earnings, utilizing the 1970 actual age-education structure; (2) the 2000 predicted earnings, using the 2000 actual age-education distribution; (3) the 2000 predicted earnings, employing the 2000 actual education composition, and the 1970 age structure; (4) and the 2000 predicted earnings, utilizing the 2000 actual age structure, and the 1970 education composition.

Table 2. Effects of Age and Education Distributions on Predicted Earnings[+] from Equation (1) by Age-Education Groups, 1970 and 2000.

Age-Education Group	**1970 Actual Predicted Earnings**	**2000 Predicted Earnings Using:**		
		2000 Actual Age-Education Distribution	**2000 Actual Education, and 1970 Age Distribution**	**2000 Actual Age, and 1970 Education Distribution**
15–24 years 0–4 years of schooling	162.81	202.03	201.81	200.53
15–24 years 5–8 years of schooling	252.41	243.73	229.60	321.10
15–24 years 9+ years of schooling	386.89	329.49	306.83	480.39
25–34 years 0–4 years of schooling	236.21	300.46	300.81	290.72
25–34 years 5–8 years of schooling	500.30	435.64	442.69	590.64
25–34 years 9+ years of schooling	905.35	796.27	808.72	1,111.79
35–49 years 0–4 years of schooling	293.24	400.16	406.05	341.30
35–49 years 5–8 years of schooling	722.59	610.31	638.24	843.60
35–49 years 9+ years of schooling	1,391.23	1,375.81	1,409.14	1,679.37
50–64 years 0–4 years of schooling	309.80	394.42	399.25	331.58
50–64 years 5–8 years of schooling	824.87	811.51	830.70	1,005.31
50–64 years 9+ years of schooling	1,556.92	1,891.74	1,892.67	1,901.83

[+] Nominal income was converted to base 1 in January 2002, taking into account changes in currency and inflation.
Source: 1970–2000 Brazilian Censuses.

Table 3. Effects of Age and Education Distributions on Predicted Earnings+ from Equation (1') by Age-Education Groups, 1970 and 2000.

Age-Education Group	1970 Actual Predicted Earnings	2000 Predicted Earnings Using: 2000 Actual Age-Education Distribution	2000 Actual Education, and 1970 Age Distribution	2000 Actual Age, and 1970 Education Distribution
15–24 years 0–4 years of schooling	161.01	206.49	204.45	192.58
15–24 years 5–8 years of schooling	254.35	268.63	245.19	409.39
15–24 years 9+ years of schooling	430.20	321.84	299.68	469.45
25–34 years 0–4 years of schooling	225.60	312.56	314.13	271.04
25–34 years 5–8 years of schooling	533.62	445.95	454.15	629.99
25–34 years 9+ years of schooling	1,040.79	812.09	815.46	887.72
35–49 years 0–4 years of schooling	269.80	404.40	414.40	310.07
35–49 years 5–8 years of schooling	788.13	609.37	642.95	898.28
35–49 years 9+ years of schooling	1,536.64	1,281.75	1,328.73	1,729.86
50–64 years 0–4 years of schooling	276.26	414.27	424.84	289.37
50–64 years 5–8 years of schooling	941.57	814.89	825.19	914.27
50–64 years 9+ years of schooling	1,687.24	1,422.78	1,469.16	2,013.55

+ Nominal income was converted to base 1 in January 2002, taking into account changes in currency and inflation.
Source: 1970–2000 Brazilian Censuses.

Analyzing the results in the third column of Tables 2 and 3, one can see that mean real earnings would have been smaller for the youngest age group (15–24), when holding age composition constant, compared to original estimates (second column). Predicted earnings are greater for the other age groups compared to original estimates, because the aging process experienced by the Brazilian population increased the share of these age groups, with a result of even smaller original predicted earnings (second column) compared to the case of age composition constant (third column).

Results from estimates holding education constant from 1970 to 2000 (fourth column) indicate that, for groups with greater levels of education (five to eight years of schooling, and at least nine years of schooling), earnings of these workers would have been larger than the original estimates at the end of the period. This provides evidence that the improvement in education attainment over time increased the share of workers with better education, lowering their income. Groups in the lowest educated level (zero to four years of schooling) would have experienced a decrease in their earnings with a constant education structure from 1970 to 2000, compared to original predictions. This fact is verified because since the lowest educated groups represented a greater share in the 1970 population compared to the 2000 population, their earnings would have fallen considerably if they remained a significant portion of the population.

In general, results in Tables 2 and 3 suggest that changes in the education distribution are the ones that generated the greatest impacts on earnings over time. When holding 1970 education composition constant (fourth column), the predicted earnings have values more unlike the original 2000 predicted earnings (second column) than when holding age composition constant (third column). Thus, changing education composition over time, within labor force ages (15–64), generated greater impacts on worker earnings than changes in age structure.

Improvements in education attainment generated lower earnings for better educated workers compared to the estimates holding education constant from 1970. However, an important result is that if the education had maintained constant over time, the lowest educated workers would have experienced even smaller earnings than illustrated by the original predictions. More specifically, earnings inequality between the least educated group (zero to four years of schooling) and the other education groups, within each age group, would have been even greater than the one predicted with the age-education composition in 2000. Thus, the improvement in education attainment from 1970 to 2000 was an important aspect towards reducing economic inequality in Brazil.

Moreover, changes in age structure also decreased earnings inequality between the youngest age group (15–24) compared to the other age groups. This assessment is supported by the finding that mean real earnings would have been smaller for the youngest age group, and bigger for the other ones, if the age composition had remained the same from 1970 to 2000. Thus, fertility decline had a central role in the reduction of income inequality in the country, because it generated a decrease in the proportion of younger groups in the labor market.

Since there is great variation in age and education compositions across Brazilian micro-regions, such as illustrated in this study, important policies to decrease even further income inequality in the country would be to improve education attainment in areas that still have large proportions of people with lower levels of schooling, as well as to promote family planning programs in regions that still have higher levels of fertility.

In order to better understand the separate impact of changing age and education compositions over time in the predicted earnings, a set of figures were estimated. The national age-education proportions, holding age composition constant from 1970 to 2000, and holding education composition constant from 1970 to 2000, were utilized for this exercise, as well as coefficients from Equations (1) and (1’).

Figures 1 to 4 plot the ratio of predicted earnings from the own-effects model (Equation (1)), and from the own-effects model interacted with year (Equation (1’)), to predicted earnings from the model that includes only indicators for age-education groups and years. The horizontal line is set to be equal to one, and shows the model that excludes the proportions in each age-education group. These figures demonstrate that groups with decreasing proportions have gains in earnings, and those with growing proportions experience a decline in earnings over time.

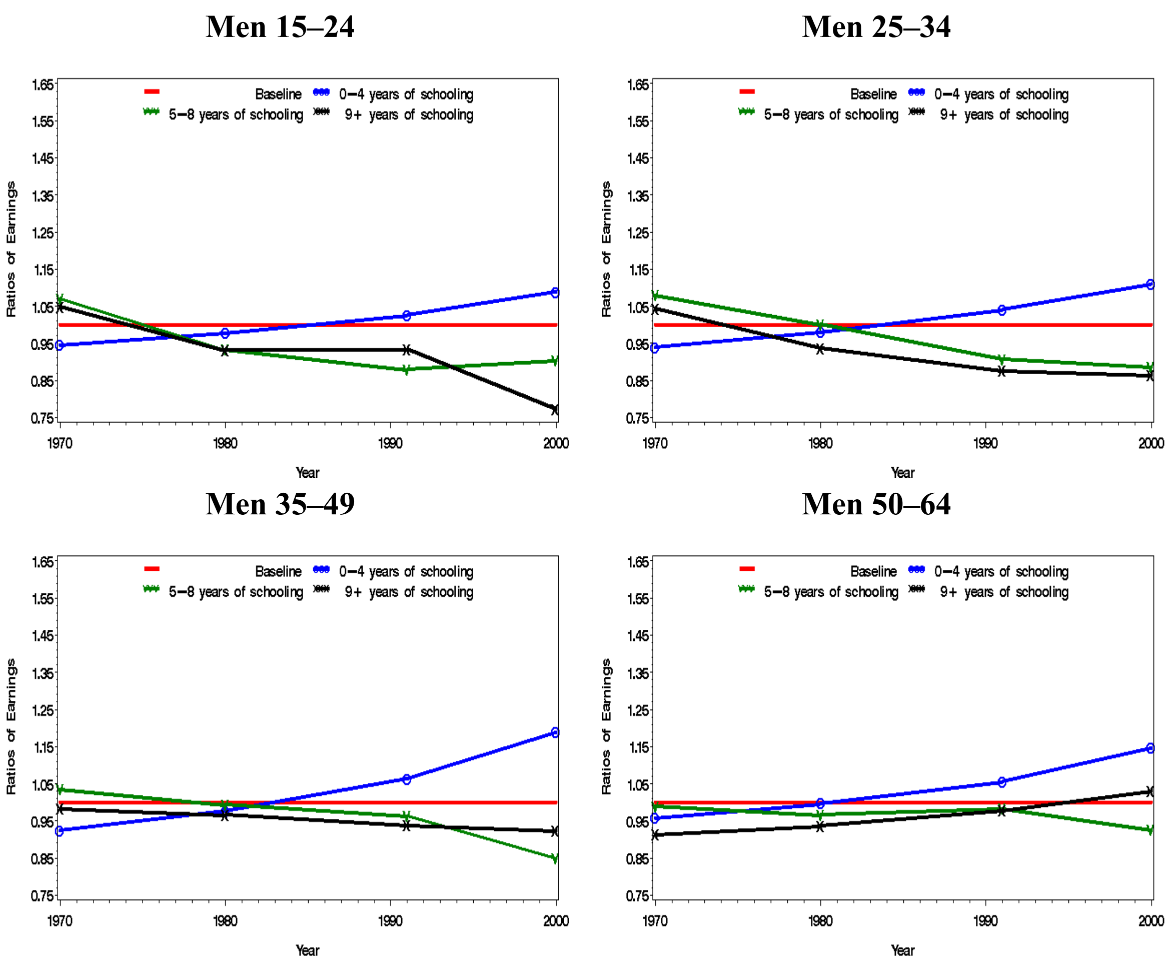
Figures 1 illustrates estimates from the own-effects model (Equation (1)), holding national age distribution constant from 1970 to 2000; Figure 2 shows estimates from Equation (1), holding national education distribution constant from 1970 to 2000; Figure 3 demonstrates predictions from own-effects model interacted with year indicators (Equation (1')), holding age distribution constant; and Figure 4 shows estimates from Equation (1'), holding education distribution constant.

Figure 1 indicates that, holding age composition constant from 1970 to 2000, the ratios of predicted earnings from Equation (1) to the baseline model would be lower for the lowest age group (15–24) compared to results without holding age composition constant (not shown). On the other hand, older age groups (35–49 and 50–64) have higher ratios than the previous results. These patterns show that maintaining a younger age composition constant over time, would decrease the earnings of younger males, and increase those of older males.

The general tendency illustrated in Figure 2 is that ratios for the lowest educated group (zero to four years of schooling) are smaller compared to results without holding education constant (not shown), and ratios for the groups with higher education are bigger than in the previous results. These findings demonstrate that, keeping education distribution constant from 1970 to 2000, estimates from Equation (1) will have greater negative impacts for the group with bigger proportions in 1970 (zero to four years of schooling), than for education groups with smaller proportions at the beginning of the period.

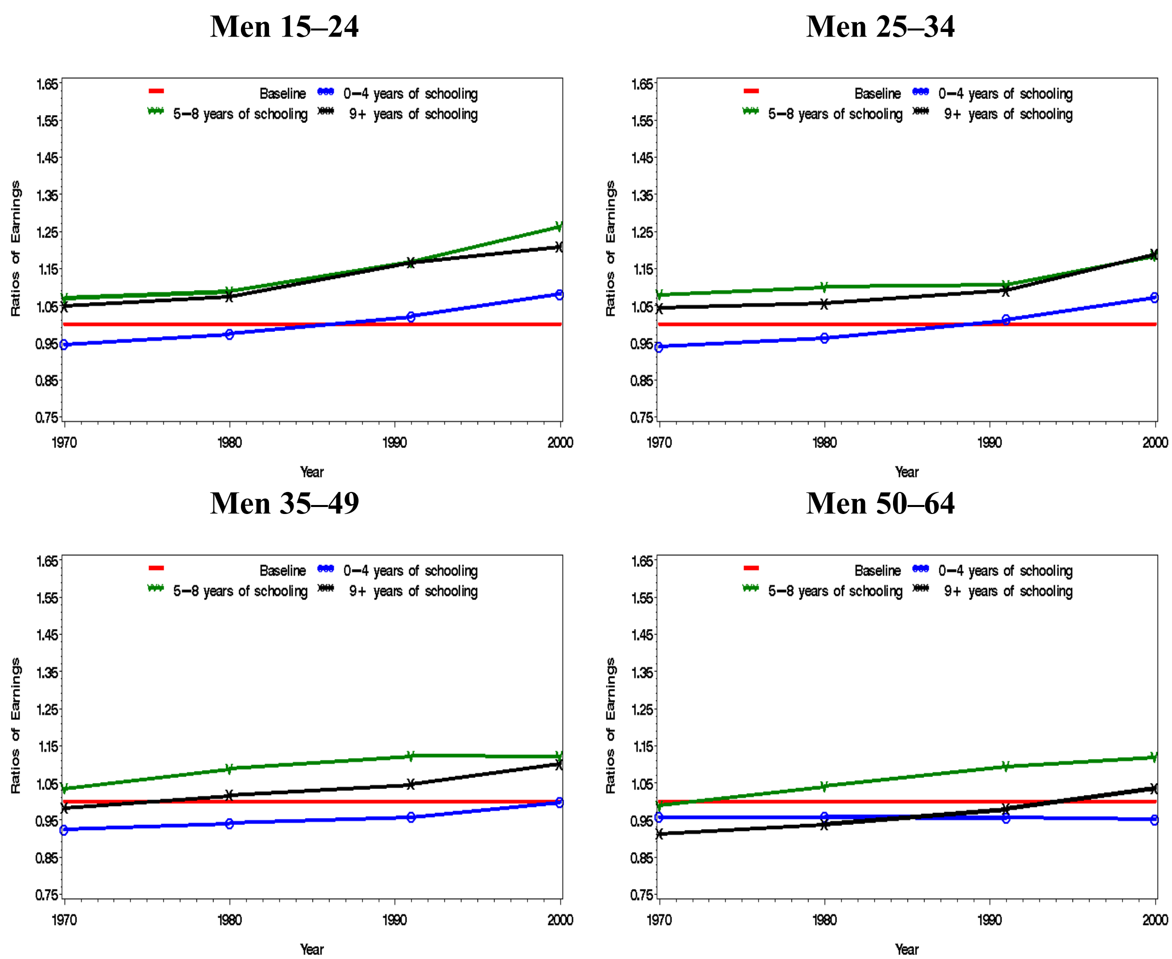
Figures 3 and 4 illustrate results from Equation (1'). Figure 1 indicated that holding the younger age composition in 1970 constant, it would decrease earnings of younger males, and increase earnings in older groups. When interactions of year indicators with age-education group proportions are included in the model, the new results in Figure 3 suggest that the gains and losses in predicted ratios for the several age-education groups have a similar pattern to the original estimates (not shown). Figure 4 shows predicted ratios holding education distribution constant from 1970 to 2000. In this case, it is clear that for the education group (zero to four years of schooling) that had greater proportions in 1970, the new predicted earnings are lower compared to the ones without holding education constant (not shown). On the other hand, groups with lower proportions in 1970 (five to eight years of schooling, and at least nine years of schooling) have higher predicted ratios than previous results.

Figure 1. Ratios of Predicted Earnings from Equation (1) to Predicted Earnings from Baseline Model, using the National Age-Education Distribution, and Maintaining the 1970 Age Distribution Constant, 1970–2000.



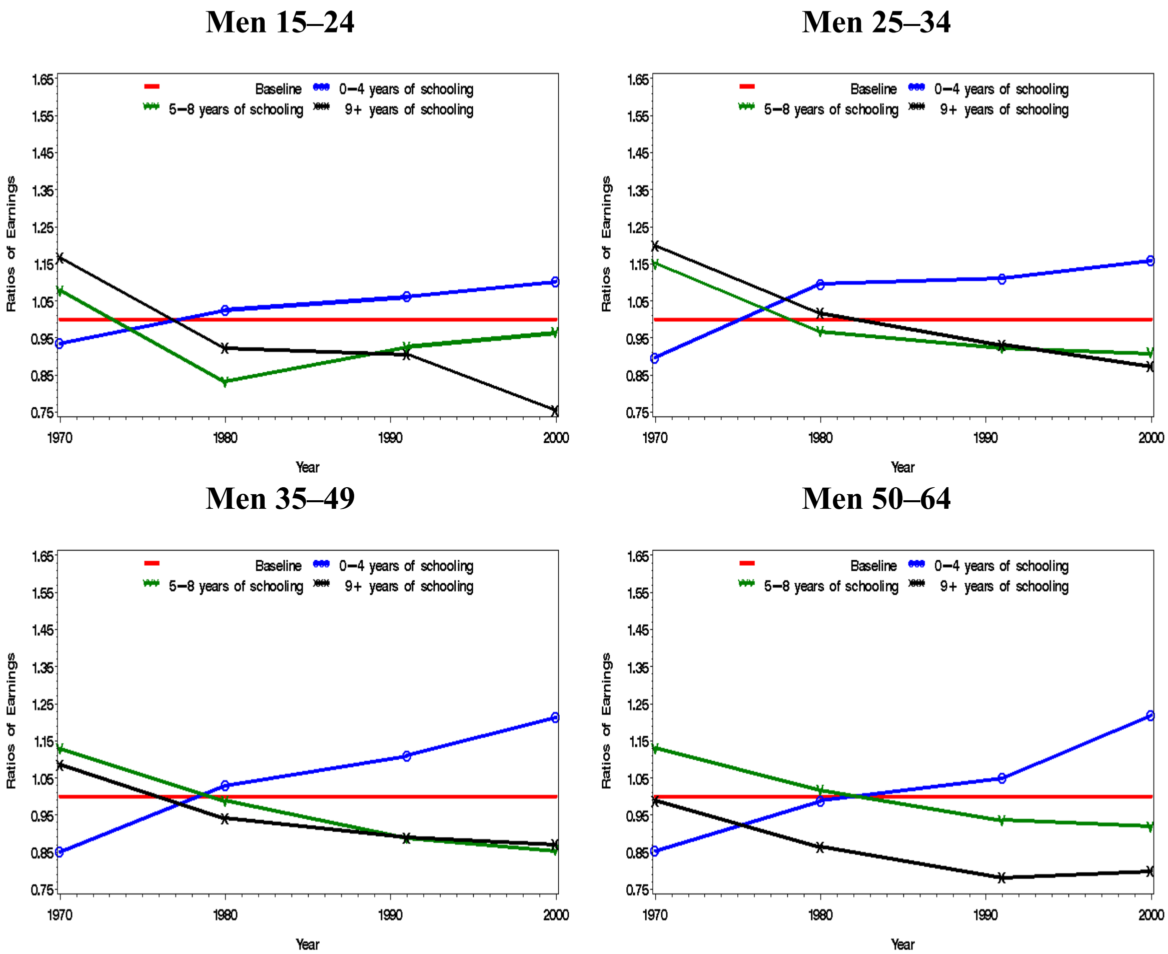
Source: 1970–2000 Brazilian Censuses.

Figure 2. Ratios of Predicted Earnings from Equation (1) to Predicted Earnings from Baseline Model, using the National Age-Education Distribution, and Maintaining the 1970 Education Distribution Constant, 1970–2000.



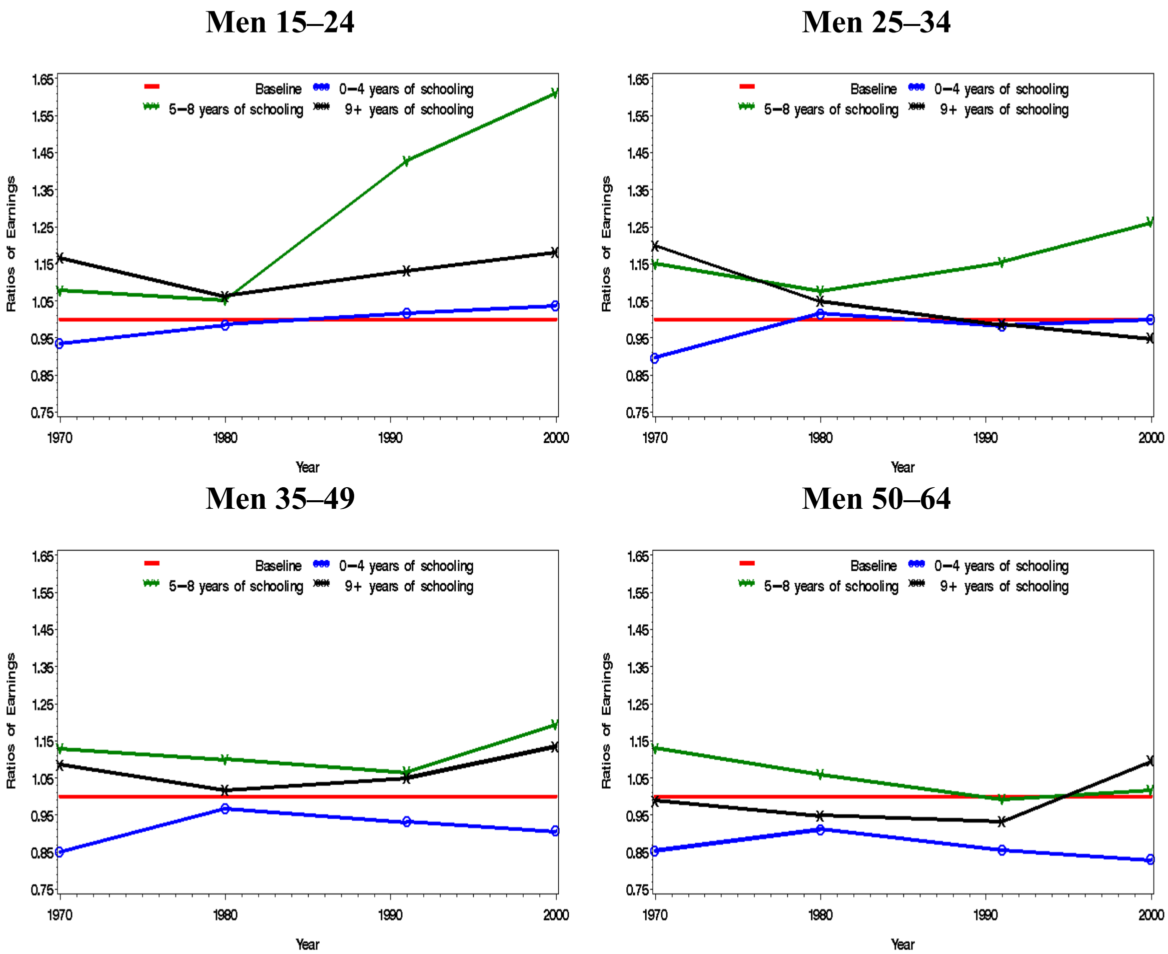
Source: 1970–2000 Brazilian Censuses.

Figure 3. Ratios of Predicted Earnings from Equation (1’) to Predicted Earnings from Baseline Model, using the National Age-Education Distribution, and Maintaining the 1970 Age Distribution Constant, 1970–2000.



Source: 1970–2000 Brazilian Censuses.

Figure 4. Ratios of Predicted Earnings from Equation (1') to Predicted Earnings from Baseline Model, using the National Age-Education Distribution, and Maintaining the 1970 Education Distribution Constant, 1970–2000.



Source: 1970–2000 Brazilian Censuses.

Inequality of income distribution among age-education groups

Calculations of Gini coefficients are presented in the following tables in order to measure the inequality of the income distribution among age-education groups. The income is more equally distributed among groups, when the coefficient is closer to zero. When the coefficient is closer to one, the income is more unequally distributed. A coefficient equal to zero corresponds to perfect income equality, i.e. everyone has the same income. A coefficient equal to one indicates a perfect income inequality, i.e. one group has all the income, while everyone else has zero income.

These coefficients are a more appropriate measure to estimate income inequality than the predicted earnings presented in Tables 2 and 3. This improvement happens because Gini coefficients take into account not only the income distributions presented in Tables 2 and 3, but also the specific national age-education distributions used to calculate those predicted earnings.

More specifically, Gini coefficients that used predicted national earnings from Equation (1) in Table 2, utilized: (1) in Tables 4 and 5, original national age-education distribution; (2) in Table 6, national age-education distribution, holding age composition constant from 1970 to 2000; and (3) in Table 7, national age-education distribution, maintaining education composition constant from 1970 to 2000.

The estimates from Equation (1') in Table 3 were used to calculate Gini coefficients: (1) in Tables 8 and 9, with original national age-education distribution; (2) in Table 10, using national age-education distribution, maintaining age composition constant from 1970 to 2000; and (3) in Table 11, utilizing national age-education composition, holding education distribution constant from 1970 to 2000.

Table 4. Gini Coefficient Calculation Using Predicted National Earnings[+] from Equation (1) and National Age-Education Distribution, 1970.

Age-Education Group	Income Table 2 (column 1)	Income Distribution	Original Age-Educ. Distribution	Cumulative Income	Cumulative Age-Educ. Distribution	$(e_i)*(d_{i+1})$	$(d_i)*(e_{i+1})$
	(a)	(b)	(c)	(d)	(e)	(f)	(g)
15–24 years 0–4 years of schooling	162.81	0.022	0.282	0.022	0.282	0.016	0.007
15–24 years 5–8 years of schooling	252.41	0.033	0.054	0.055	0.336	0.036	0.020
15–24 years 9+ years of schooling	386.89	0.051	0.027	0.106	0.363	0.050	0.060
25–34 years 0–4 years of schooling	236.21	0.031	0.197	0.138	0.560	0.114	0.080
25–34 years 5–8 years of schooling	500.30	0.066	0.020	0.204	0.580	0.188	0.122
25–34 years 9+ years of schooling	905.35	0.120	0.020	0.324	0.600	0.218	0.268
35–49 years 0–4 years of schooling	293.24	0.039	0.227	0.363	0.827	0.379	0.306
35–49 years 5–8 years of schooling	722.59	0.096	0.016	0.459	0.843	0.542	0.394
35–49 years 9+ years of schooling	1,391.23	0.184	0.016	0.643	0.859	0.588	0.635
50–64 years 0–4 years of schooling	309.80	0.041	0.128	0.684	0.987	0.784	0.680
50–64 years 5–8 years of schooling	824.87	0.109	0.007	0.794	0.994	0.994	0.794
50–64 years 9+ years of schooling	1,556.92	0.206	0.006	1.000	1.000	—	—
Total	**7,542.62**	**1.0**	**1.0**	**—**	**—**	**3.908**	**3.365**
				Gini Coefficient [sum(f)-sum(g)]=		**0.542**	

[+] Nominal income was converted to base 1 in January 2002, taking into account changes in currency and inflation.
Source: 1970–2000 Brazilian Censuses.

Table 5. Gini Coefficient Calculation Using Predicted National Earnings[+] from Equation (1) and National Age-Education Distribution, 2000.

Age-Education Group	**Income Table 2 (column 2)**	**Income Distribution**	**Original Age-Educ. Distribution**	**Cumulative Income**	**Cumulative Age-Educ. Distribution**	**$(e_i)*(d_{i+1})$**	**$(d_i)*(e_{i+1})$**
	(a)	**(b)**	**(c)**	**(d)**	**(e)**	**(f)**	**(g)**
15–24 years 0–4 years of schooling	202.03	0.026	0.090	0.026	0.090	0.005	0.006
15–24 years 5–8 years of schooling	243.73	0.031	0.125	0.057	0.215	0.021	0.018
15–24 years 9+ years of schooling	329.49	0.042	0.102	0.099	0.317	0.044	0.040
25–34 years 0–4 years of schooling	300.46	0.039	0.088	0.138	0.406	0.079	0.067
25–34 years 5–8 years of schooling	435.64	0.056	0.076	0.194	0.482	0.143	0.109
25–34 years 9+ years of schooling	796.27	0.102	0.081	0.296	0.563	0.196	0.206
35–49 years 0–4 years of schooling	400.16	0.051	0.133	0.348	0.696	0.296	0.265
35–49 years 5–8 years of schooling	610.31	0.078	0.067	0.426	0.764	0.460	0.361
35–49 years 9+ years of schooling	1,375.81	0.177	0.085	0.602	0.848	0.554	0.573
50–64 years 0–4 years of schooling	394.42	0.051	0.104	0.653	0.952	0.721	0.635
50–64 years 5–8 years of schooling	811.51	0.104	0.020	0.757	0.972	0.972	0.757
50–64 years 9+ years of schooling	1,891.74	0.243	0.028	1.000	1.000	—	—
Total	**7,791.57**	**1.0**	**1.0**	**—**	**—**	**3.490**	**3.038**
				Gini Coefficient [sum(f)-sum(g)]=		**0.452**	

[+] Nominal income was converted to base 1 in January 2002, taking into account changes in currency and inflation.
Source: 1970–2000 Brazilian Censuses.

Table 6. Gini Coefficient Calculation Using Predicted National Earnings[+] from Equation (1) and National Age-Education Distribution, and Maintaining the 1970 Age Distribution Constant, 2000.

Age-Education Group	**Income Table 2 (column 3)**	**Income Distribution**	**Age-Educ. Distribution (1970 Age)**	**Cumulative Income**	**Cumulative Age-Educ. Distribution**	**$(e_i)*(d_{i+1})$**	**$(d_i)*(e_{i+1})$**
	(a)	**(b)**	**(c)**	**(d)**	**(e)**	**(f)**	**(g)**
15–24 years 0–4 years of schooling	201.81	0.026	0.103	0.026	0.103	0.006	0.006
15–24 years 5–8 years of schooling	229.60	0.029	0.143	0.055	0.246	0.023	0.020
15–24 years 9+ years of schooling	306.83	0.039	0.117	0.094	0.363	0.048	0.042
25–34 years 0–4 years of schooling	300.81	0.038	0.085	0.132	0.448	0.084	0.069
25–34 years 5–8 years of schooling	442.69	0.056	0.074	0.188	0.522	0.152	0.113
25–34 years 9+ years of schooling	808.72	0.103	0.078	0.291	0.600	0.206	0.210
35–49 years 0–4 years of schooling	406.05	0.052	0.121	0.343	0.721	0.306	0.268
35–49 years 5–8 years of schooling	638.24	0.081	0.061	0.424	0.782	0.472	0.364
35–49 years 9+ years of schooling	1,409.14	0.179	0.077	0.603	0.859	0.562	0.576
50–64 years 0–4 years of schooling	399.25	0.051	0.096	0.654	0.955	0.725	0.637
50–64 years 5–8 years of schooling	830.70	0.106	0.018	0.759	0.974	0.974	0.759
50–64 years 9+ years of schooling	1,892.67	0.241	0.026	1.000	1.000	—	—
Total	**7,866.51**	**1.0**	**1.0**	—	—	**3.557**	**3.064**
				Gini Coefficient [sum(f)-sum(g)]=		**0.492**	

[+] Nominal income was converted to base 1 in January 2002, taking into account changes in currency and inflation.
Source: 1970–2000 Brazilian Censuses.

Table 7. Gini Coefficient Calculation Using Predicted National Earnings[+] from Equation (1) and National Age-Education Distribution, and Maintaining the 1970 Education Distribution Constant, 2000.

Age-Education Group	Income Table 2 (column 4)	Income Distribution	Age-Educ. Distribution (1970 Educ.)	Cumulative Income	Cumulative Age-Educ. Distribution	$(e_i)*(d_{i+1})$	$(d_i)*(e_{i+1})$
	(a)	(b)	(c)	(d)	(e)	(f)	(g)
15–24 years 0–4 years of schooling	200.53	0.022	0.182	0.022	0.182	0.010	0.005
15–24 years 5–8 years of schooling	321.10	0.035	0.042	0.057	0.223	0.025	0.014
15–24 years 9+ years of schooling	480.39	0.053	0.024	0.110	0.247	0.035	0.047
25–34 years 0–4 years of schooling	290.72	0.032	0.177	0.142	0.424	0.088	0.064
25–34 years 5–8 years of schooling	590.64	0.065	0.026	0.207	0.450	0.148	0.097
25–34 years 9+ years of schooling	1,111.79	0.122	0.019	0.329	0.469	0.172	0.242
35–49 years 0–4 years of schooling	341.30	0.038	0.267	0.367	0.736	0.338	0.278
35–49 years 5–8 years of schooling	843.60	0.093	0.023	0.459	0.759	0.489	0.358
35–49 years 9+ years of schooling	1,679.37	0.185	0.020	0.644	0.779	0.530	0.635
50–64 years 0–4 years of schooling	331.58	0.036	0.208	0.680	0.987	0.780	0.676
50–64 years 5–8 years of schooling	1,005.31	0.110	0.007	0.791	0.993	0.993	0.791
50–64 years 9+ years of schooling	1,901.83	0.209	0.007	1.000	1.000	—	—
Total	**9,098.16**	**1.0**	**1.0**	—	—	**3.609**	**3.208**
				Gini Coefficient [sum(f)-sum(g)]=		**0.401**	

[+] Nominal income was converted to base 1 in January 2002, taking into account changes in currency and inflation.
Source: 1970–2000 Brazilian Censuses.

Table 8. Gini Coefficient Calculation Using Predicted National Earnings[+] from Equation (1') and National Age-Education Distribution, 1970.

Age-Education Group	Income Table 3 (column 1)	Income Distribution	Original Age-Educ. Distribution	Cumulative Income	Cumulative Age-Educ. Distribution	$(e_i)*(d_{i+1})$	$(d_i)*(e_{i+1})$
	(a)	(b)	(c)	(d)	(e)	(f)	(g)
15–24 years 0–4 years of schooling	161.01	0.020	0.282	0.020	0.282	0.014	0.007
15–24 years 5–8 years of schooling	254.35	0.031	0.054	0.051	0.336	0.035	0.019
15–24 years 9+ years of schooling	430.20	0.053	0.027	0.104	0.363	0.048	0.058
25–34 years 0–4 years of schooling	225.60	0.028	0.197	0.132	0.560	0.110	0.076
25–34 years 5–8 years of schooling	533.62	0.066	0.020	0.197	0.580	0.188	0.118
25–34 years 9+ years of schooling	1,040.79	0.128	0.020	0.325	0.600	0.215	0.269
35–49 years 0–4 years of schooling	269.80	0.033	0.227	0.358	0.827	0.376	0.302
35–49 years 5–8 years of schooling	788.13	0.097	0.016	0.455	0.843	0.542	0.391
35–49 years 9+ years of schooling	1,536.64	0.189	0.016	0.643	0.859	0.582	0.635
50–64 years 0–4 years of schooling	276.26	0.034	0.128	0.677	0.987	0.783	0.673
50–64 years 5–8 years of schooling	941.57	0.116	0.007	0.793	0.994	0.994	0.793
50–64 years 9+ years of schooling	1,687.24	0.207	0.006	1.000	1.000	—	—
Total	**8,145.21**	**1.0**	**1.0**	—	—	**3.887**	**3.340**
				Gini Coefficient [sum(f)-sum(g)]=		**0.547**	

[+] Nominal income was converted to base 1 in January 2002, taking into account changes in currency and inflation.
Source: 1970–2000 Brazilian Censuses.

Table 9. Gini Coefficient Calculation Using Predicted National Earnings[+] from Equation (1') and National Age-Education Distribution, 2000.

Age-Education Group	Income Table 3 (column 2)	Income Distribution	Original Age-Educ. Distribution	Cumulative Income	Cumulative Age-Educ. Distribution	$(e_i)*(d_{i+1})$	$(d_i)*(e_{i+1})$
	(a)	(b)	(c)	(d)	(e)	(f)	(g)
15–24 years 0–4 years of schooling	206.49	0.028	0.090	0.028	0.090	0.006	0.006
15–24 years 5–8 years of schooling	268.63	0.037	0.125	0.065	0.215	0.023	0.021
15–24 years 9+ years of schooling	321.84	0.044	0.102	0.109	0.317	0.048	0.044
25–34 years 0–4 years of schooling	312.56	0.043	0.088	0.152	0.406	0.086	0.073
25–34 years 5–8 years of schooling	445.95	0.061	0.076	0.213	0.482	0.156	0.120
25–34 years 9+ years of schooling	812.09	0.111	0.081	0.324	0.563	0.213	0.225
35–49 years 0–4 years of schooling	404.40	0.055	0.133	0.379	0.696	0.322	0.289
35–49 years 5–8 years of schooling	609.37	0.083	0.067	0.462	0.764	0.487	0.392
35–49 years 9+ years of schooling	1,281.75	0.175	0.085	0.637	0.848	0.589	0.607
50–64 years 0–4 years of schooling	414.27	0.057	0.104	0.694	0.952	0.767	0.674
50–64 years 5–8 years of schooling	814.89	0.111	0.020	0.805	0.972	0.972	0.805
50–64 years 9+ years of schooling	1,422.78	0.195	0.028	1.000	1.000	—	—
Total	**7,315.02**	**1.0**	**1.0**	**—**	**—**	**3.668**	**3.257**
				Gini Coefficient [sum(f)-sum(g)]=		**0.411**	

[+] Nominal income was converted to base 1 in January 2002, taking into account changes in currency and inflation.
Source: 1970–2000 Brazilian Censuses.

Table 10. Gini Coefficient Calculation Using Predicted National Earnings[+] from Equation (1') and National Age-Education Distribution, and Maintaining the 1970 Age Distribution Constant, 2000.

Age-Education Group	**Income Table 3 (column 3)**	**Income Distribution**	**Age-Educ. Distribution (1970 Age)**	**Cumulative Income**	**Cumulative Age-Educ. Distribution**	**$(e_i)*(d_{i+1})$**	**$(d_i)*(e_{i+1})$**
	(a)	**(b)**	**(c)**	**(d)**	**(e)**	**(f)**	**(g)**
15–24 years 0–4 years of schooling	204.45	0.027	0.103	0.027	0.103	0.006	0.007
15–24 years 5–8 years of schooling	245.19	0.033	0.143	0.060	0.246	0.025	0.022
15–24 years 9+ years of schooling	299.68	0.040	0.117	0.101	0.363	0.052	0.045
25–34 years 0–4 years of schooling	314.13	0.042	0.085	0.143	0.448	0.091	0.075
25–34 years 5–8 years of schooling	454.15	0.061	0.074	0.204	0.522	0.164	0.122
25–34 years 9+ years of schooling	815.46	0.110	0.078	0.314	0.600	0.222	0.226
35–49 years 0–4 years of schooling	414.40	0.056	0.121	0.369	0.721	0.329	0.289
35–49 years 5–8 years of schooling	642.95	0.086	0.061	0.456	0.782	0.496	0.391
35–49 years 9+ years of schooling	1,328.73	0.179	0.077	0.634	0.859	0.594	0.606
50–64 years 0–4 years of schooling	424.84	0.057	0.096	0.692	0.955	0.766	0.673
50–64 years 5–8 years of schooling	825.19	0.111	0.018	0.802	0.974	0.974	0.802
50–64 years 9+ years of schooling	1,469.16	0.198	0.026	1.000	1.000	—	—
Total	**7,438.31**	**1.0**	**1.0**	—	—	**3.719**	**3.259**
					Gini Coefficient [sum(f)-sum(g)]=	**0.459**	

[+] Nominal income was converted to base 1 in January 2002, taking into account changes in currency and inflation.
Source: 1970–2000 Brazilian Censuses.

Table 11. Gini Coefficient Calculation Using Predicted National Earnings+ from Equation (1') and National Age-Education Distribution, and Maintaining the 1970 Education Distribution Constant, 2000.

Age-Education Group	**Income Table 3 (column 4)**	**Income Distribution**	**Age-Educ. Distribution (1970 Educ.)**	**Cumulative Income**	**Cumulative Age-Educ. Distribution**	**$(e_i)*(d_{i+1})$**	**$(d_i)*(e_{i+1})$**
	(a)	**(b)**	**(c)**	**(d)**	**(e)**	**(f)**	**(g)**
15–24 years 0–4 years of schooling	192.58	0.021	0.182	0.021	0.182	0.012	0.005
15–24 years 5–8 years of schooling	409.39	0.045	0.042	0.067	0.223	0.027	0.017
15–24 years 9+ years of schooling	469.45	0.052	0.024	0.119	0.247	0.037	0.050
25–34 years 0–4 years of schooling	271.04	0.030	0.177	0.149	0.424	0.093	0.067
25–34 years 5–8 years of schooling	629.99	0.070	0.026	0.219	0.450	0.143	0.103
25–34 years 9+ years of schooling	887.72	0.098	0.019	0.317	0.469	0.165	0.234
35–49 years 0–4 years of schooling	310.07	0.034	0.267	0.352	0.736	0.332	0.267
35–49 years 5–8 years of schooling	898.28	0.100	0.023	0.451	0.759	0.488	0.351
35–49 years 9+ years of schooling	1,729.86	0.192	0.020	0.643	0.779	0.526	0.635
50–64 years 0–4 years of schooling	289.37	0.032	0.208	0.675	0.987	0.766	0.671
50–64 years 5–8 years of schooling	914.27	0.101	0.007	0.777	0.993	0.993	0.777
50–64 years 9+ years of schooling	2,013.55	0.223	0.007	1.000	1.000	—	—
Total	**9,015.57**	**1.0**	**1.0**	—	—	**3.582**	**3.175**
					Gini Coefficient [sum(f)-sum(g)]=	**0.407**	

+ Nominal income was converted to base 1 in January 2002, taking into account changes in currency and inflation.
Source: 1970–2000 Brazilian Censuses.

Table 12 summarizes all Gini coefficients estimated above. These results indicate that the income inequality decreased from 1970 to 2000 among the 12 age-education groups. If the age composition had remained the same from 1970 to 2000, the income inequality would have experienced a smaller decrease than the one observed when both age and education changed over time. In the case of education composition constant from 1970 to 2000, the income inequality would have decreased even more in the period. These numbers show that population aging had an important impact in the reduction of inequality in Brazil. Moreover, the improvement in education attainment avoided even further declines in income inequality in the country. Thus, public policies have to take into account that improvement in education attainment is necessary in order for workers to have better returns in earnings, but changes in the labor force age structure are also necessary to generate a more equal income distribution. Finally, family planning programs are essential in the reduction of inequality in Brazil, because they would decrease the proportion of younger workers entering the labor market in future years.

Table 12. Summary of Gini Coefficients Using Predicted National Earnings from Equations (1) and (1') and National Age-Education Distributions, 1970 and 2000.

Models	**Gini Coefficients Using National Distribution from:**			
	1970	**2000**	**1970 Age; 2000 Education**	**1970 Education; 2000 Age**
Equation (1): Own-effects	0.542	0.452	0.492	0.401
Equation (1'): Own-effects X Year	0.547	0.411	0.459	0.407

Source: 1970–2000 Brazilian Censuses.

Differences in the male population distribution and earnings by race

An important aspect of the Brazilian economy that has to be taken into account for public policies is related to the differences in the male population distribution in age-education groups by race. The 1970 Census does not have information on color or race characteristics of respondents. The 1980 Census has the variable "color" (*cor*) with categories "white" (*branca*), "black" (*preta*), "yellow" (*amarela* — Asian), and "brown" (*parda*). The 1991 and 2000 Censuses added the category "indigenous" (*indígena*) to the ones available in the 1980 Census, and identify the variable as "color or race" (*cor ou raça*). Here this variable will be denominated as race.

Wood and Carvalho (1994) and Carvalho *et al* (2003) indicated that the brown category had a growth over time above the expected vegetative growth. They suspect that because the black population experienced economic improvement through the years, and due to the stereotype of poverty associated to the black race, they might have identified themselves as brown. Moreover, the black identification seems to be increasing in recent years, perhaps due to the ideological work done by black civil equality movements in the 1990s. Further, maybe due to the decline in the stereotype of being brown, people who identified themselves as white in the past are now classifying their race as brown. Because of the instability in the race classification over time, brown and black categories are usually aggregated in one single category. This aggregation is called "non-white" in this study. People classified as yellow or indigenous are not included in the following analysis, because they constitute a small proportion in the population. Among males between 15 and 64 years of age, only 0.69 percent were classified as yellow in 1980, 0.50 in 1991 and 0.49 in 2000. The indigenous group varied from 0.18 percent in 1991 to 0.42 percent in 2000, indicating that this group might also have problems with self-identification.

Table 13 presents the male population distribution by age-education group and race from 1980 to 2000. The proportion of males in the lowest education group (zero to four years of schooling) has been decreasing over time, and the proportion in the other groups have been increasing over time.

Further, the distribution by race illustrates that there is a higher proportion of non-white population in the lowest education group, for all age groups, compared to the white population. Related to this pattern, the proportion of white population is bigger in the groups with five to eight years of schooling and at least nine years of schooling, compared to non-whites.

Table 14 gives an idea about the mean real monthly earnings of the male population by age-education group and race from 1980 to 2000. Levels and patterns of mean earnings might be influenced by drastic variations among individuals, within each age-education group. However, even with this limitation, Table 14 is a tool which provides an idea about earnings differences between non-whites and whites. In all age-education groups for all Censuses, earnings for white males are greater than the ones observed for black males.

Analyzing Tables 13 and 14 in conjunction with the findings presented in this study, one might say that public policies would have to take into account that changes in the age-education composition has been occurring in different levels for non-whites compared to whites. Policies would then have to target groups that are experiencing slower fertility decline, slower improvements in educational attainment, as well as lower earnings — the non-whites. Finally, as suggested by the differences across areas in the country, such policies should concentrate their effort on the non-whites living in areas with slower transitions in age-education structure.

Table 13. Percent of Male Population by Year, Race, and Age-Education Group, 1980–2000.

Age-education Group	**1980**		**1991**		**2000**	
	Non-White	**White**	**Non-White**	**White**	**Non-White**	**White**
15–24 years 0–4 years of schooling	26.87	15.98	19.93	9.77	12.99	5.60
15–24 years 5–8 years of schooling	9.07	11.68	11.82	12.44	13.74	11.41
15–24 years 9+ years of schooling	3.00	7.93	3.96	7.77	7.47	12.62
25–34 years 0–4 years of schooling	18.96	14.55	15.16	9.93	11.36	6.64
25–34 years 5–8 years of schooling	3.20	4.42	6.32	7.35	7.80	7.53
25–34 years 9+ years of schooling	2.33	6.49	4.66	9.86	5.89	10.02
35–49 years 0–4 years of schooling	21.06	17.54	19.02	15.43	15.68	11.36
35–49 years 5–8 years of schooling	1.63	2.93	3.06	4.22	6.21	7.22
35–49 years 9+ years of schooling	1.08	4.08	2.96	7.76	5.15	11.22
50–64 years 0–4 years of schooling	12.07	11.48	11.67	11.33	10.80	9.99
50–64 years 5–8 years of schooling	0.47	1.28	0.78	1.50	1.60	2.32
50–64 years 9+ years of schooling	0.26	1.63	0.67	2.62	1.32	4.06
Total	**13,969,010**	**18,294,096**	**20,551,988**	**22,446,044**	**24,182,946**	**28,176,560**

Source: 1980–2000 Brazilian Censuses.

Table 14. Mean Real Monthly Earnings of Male Population by Year, Race, and Age-Education Group, 1980–2000[+].

Age-education Group	1980		1991		2000	
	Non-White	White	Non-White	White	Non-White	White
15–24 years 0–4 years of schooling	282.94	360.77	194.17	253.82	201.80	265.01
15–24 years 5–8 years of schooling	392.69	464.48	297.25	370.56	268.65	334.36
15–24 years 9+ years of schooling	610.86	794.27	451.21	626.01	387.03	533.69
25–34 years 0–4 years of schooling	438.47	637.92	294.35	417.23	298.74	409.67
25–34 years 5–8 years of schooling	767.17	1,060.20	490.09	652.96	465.18	619.49
25–34 years 9+ years of schooling	1,320.87	2,165.86	863.60	1,390.95	779.24	1,327.54
35–49 years 0–4 years of schooling	487.97	826.58	368.88	587.85	376.62	570.53
35–49 years 5–8 years of schooling	1,061.73	1,654.57	712.56	1,034.82	621.95	889.83
35–49 years 9+ years of schooling	2,059.90	3,535.43	1,442.33	2,409.82	1,311.60	2,328.44
50–64 years 0–4 years of schooling	440.25	804.08	330.03	581.17	380.09	649.22
50–64 years 5–8 years of schooling	1,134.47	1,911.23	778.03	1,288.33	698.79	1,232.89
50–64 years 9+ years of schooling	2,301.26	3,935.86	1,846.48	3,037.60	1,717.11	3,325.95
Total	**490.89**	**1,023.34**	**418.37**	**873.96**	**484.31**	**1,025.90**

[+] Nominal income was converted to base 1 in January 2002, taking into account changes in currency and inflation.
Source: 1980–2000 Brazilian Censuses.

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