The Effect of Brazilian Demographic Change on Inequality

Simone Wajnman[1]
Naércio Menezes-Filho[2]

1) Introduction

Several studies have examined the effect of cohort size on inequality. The main hypothesis underlying these studies is that "fat cohorts tend to get low rewards" as Higgins and Williamson (1999) bluntly put it. This means that when fat cohorts are in the beginning of the age-earnings curve, where life-cycle income tend to be the lowest, this labor market glut lowers income of young workers, thus tending to heightening the slope of the age-earnings curve. Therefore, earnings inequality tends to be high. On the other hand, when large cohorts are in the middle of working life cycle, where income is the highest, the supply effect flattens the slope of age-earning curve, resulting in moderated earning inequality (Higgins, Williamson, 1999:2). This demographic hypothesis has a long tradition, especially in the United States, starting with the entry of the baby boomers into the labor market.[3] Recently, some studies have used similar arguments to point out the effect of aging on inequality. [4]

Additionally, trying to explain the exceptionally high level of inequality in Brazil, some studies have highlighted the role of the inequality of education distribution among Brazilian workers. Beyond the fact that labor markets pay different earnings for different workers, the point is that high educational inequality causes high returns to education, especially between older workers, explaining such elevated wage inequality. Barros et al. (2000) have argued that it is precisely when the education level reaches intermediate values that there is scope for high educational heterogeneity. In such transitional case, a significant fraction of older people remains illiterate while the younger population is reaching high levels of education. In addition, if the population is aging fast, the result is a increasing proportion of older and unskilled workers in the labor force.

So, this paper attempts to investigate the relationship between the dynamics of aging, education expansion and earnings inequality in Brazil. At the same time that the country is experiencing an intense population aging process, an educational transition is taking place as younger cohorts are reaching the labor market with much higher levels of education than the precedent cohorts. Thus, the proposal is to investigate the role of the demographic and educational transitions on the Brazilian earnings distribution. The hypothesis is that, while older and less educated workers are representing the largest proportion of the labor supply, the effects of high returns to education and lower returns to work experience tend to contribute to high inequality. However, when demographic and educational transitions are completed, the increased average age of the Brazilian

[1] Federal University of Minas Gerais, Brazil.
[2] University of São Paulo, Brazil.
[3] See Murphy, Plant, Welch (1988), Easterlin, Scahefer, Macunovich (1993), Macunovich (1998), Murphy, Plant, Welch (1986), among others.
[4] Investigating the contribution of age structure change on Brazilian inequality in the 1970s, Wajnman (1989) found a negative effect of age composition but a positive one regarding the returns to experience.

labor force at that time is likely to bring average returns to education and experience down, reducing the overall inequality.

The Brazilian case is notably interesting because the expansion of the education system is affecting almost exclusively the younger cohorts while the population aging process is increasing the proportion of the oldest and unskilled cohorts. As it is widely known, to educate older people is far from being an easy task. So, our aim is to identify the effects of these two forces in increasing the overall inequality and to forecast the changes in this picture that comes with the aging of better educated cohorts.

2) Data Description

In this paper we use a large data set consisting of repeated cross-sections of an annual household survey (PNAD), conducted each September by the Brazilian Census Bureau (IBGE), from 1977 to 1999.[5] From these data we keep only males with positive hours worked in the reference week, positive monetary remuneration and between 20 and 60 years of age. We split the sample into 05 educational groups: illiterates (0 years of schooling); incomplete lower primary education (1-3 years of schooling); complete lower primary and some upper primary education (4-7 year of schooling); complete upper primary education and (at least some) high school (8-11 years of schooling) and some college (12 and more). The sub-section below examines the change of age and education composition of our sample over time.

2.1 Changes in the Age and Educational Structures of the Brazilian Labor Force

Figure 1 reveals how the education structure of Brazilian workforce has improved over the last 20 years. The proportion of illiterates in the labor force declined from 23% in 1977 to about 12% in 1997. The proportion of workers with some primary education (1-3 years of schooling) also fell from about 28% in 1977 to 17% in 1997. On the other side, although the participation of the group with complete primary and some secondary education (4-7 years) has remained roughly constant in the period, there was a strong increase in the participation of workers with high school (8 –11) reaching in 1997 almost 30% of the workforce. The proportion of workers with college education (12+) has grown slowly, changing from 6% to about 9% between 1977 e 1997. Additionally, figures 2 to 6 show the improvement of education for all age groups in our sample. Trough these figures one can notice that the share of less educated workers (0 and 1-3 years of schooling) in the workforce has declined over time while the participation of those more educated, especially those with 8 to 11 years of schooling increased. It is important to point out that the share of college increased only for more experienced workers since people generally only reach this level of schooling around the age of 25 years. Besides, the share of workers with 4 to 7 years of schooling has increased just for middle age to older workers since the most important educational achievement for older cohorts was the conclusion of primary school (4 years of schooling).

[5] As PNAD was not conducted in 1980, 1991 (census years) nor in 1994 (for budget reasons), we interpolated the wage figures for these years using the adjacent years.

Figure 1
Labor Force Structure by Educational Groups over Time - 1977-1999

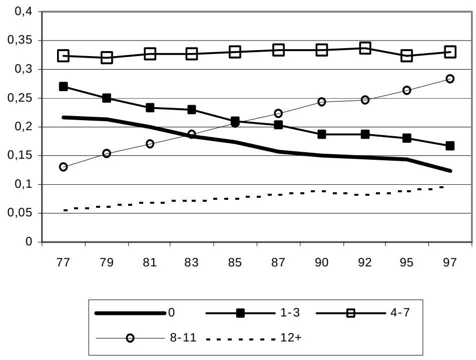


Figure 2
Proportion of Illiterates in the Labor Force in each Age Group
1977-1999

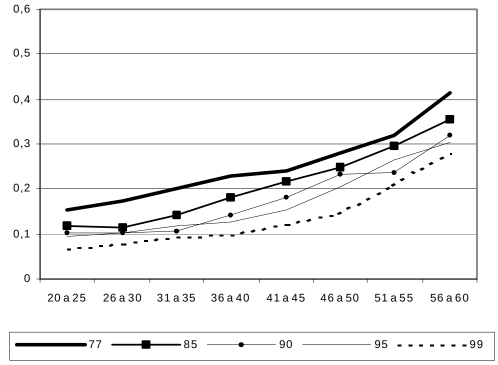


Figure 3
Proportion of Workers with 1 to 3 Years of Schooling in each Age Group
1977-1999

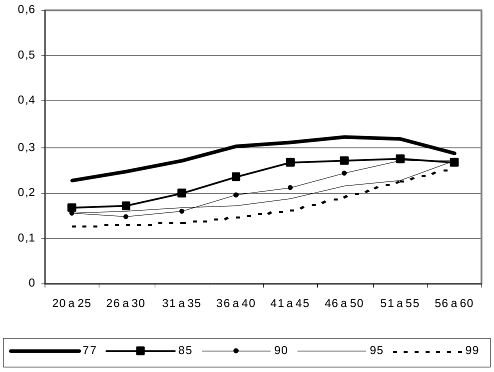


Figure 4
Proportion of Workers with 4 to 7 Years of Schooling in each Age Group
1977-1999

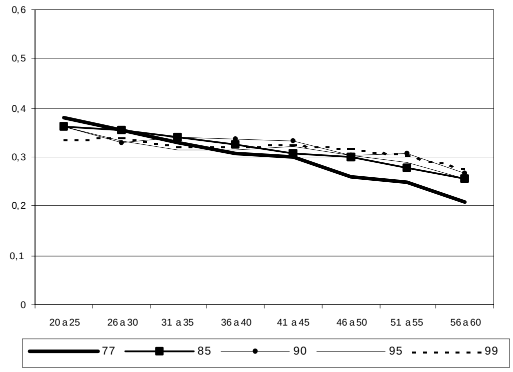


Figure 5
Proportion of Workers with 8 to 11 Years of Schooling in each Age Group
1977-1999

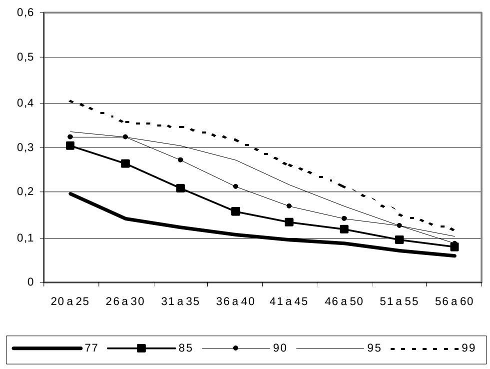
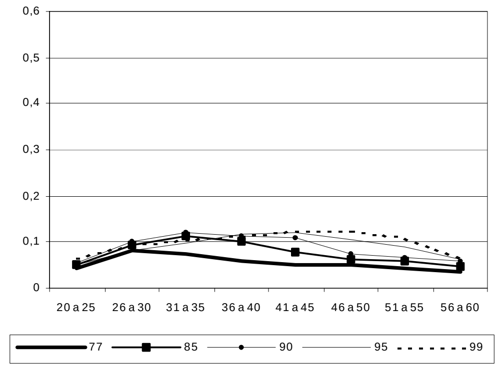


Figure 6
Proportion of Workers with 12 or more Years of Schooling in each Age Group
1977-1999



To illustrate the aging of labor force over time Figure 7 depicts age structures from 1977 to 1999. It is clear that there is a much higher proportion of middle age workers in 1997 than in 1977 when very young workers (around age 20) represented a clear majority. This is also true within each education group. As seen in Figures 8 to 12 the age profile of all age groups has became older, even though this is more evident for workers with higher level of schooling.

Figure 7
Age profile of labor force
1977 - 1999

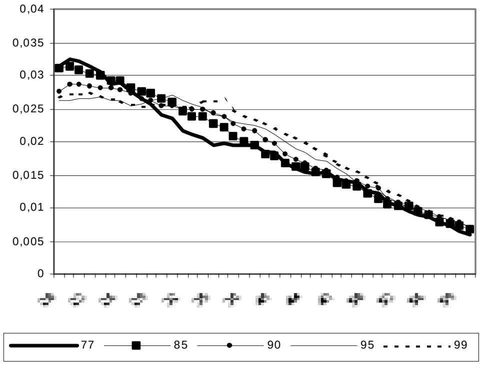


Figure 8
Age profile of illiterates
1977 - 1999

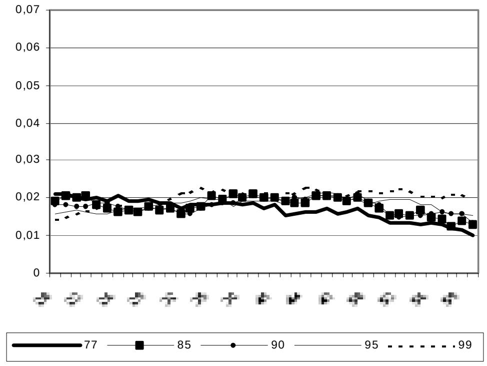


Figure 9
Age profile of 1 to 3 years of schooling
1977 - 1999

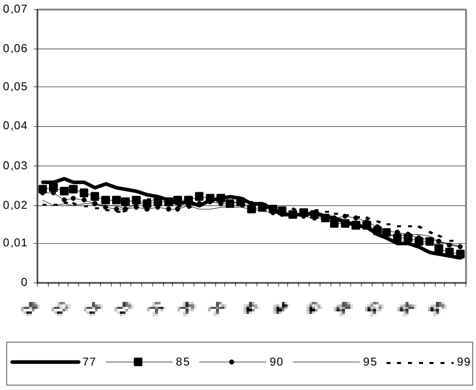


Figure 10
Age profile of 4 to 7 years of schooling
1977 - 1999

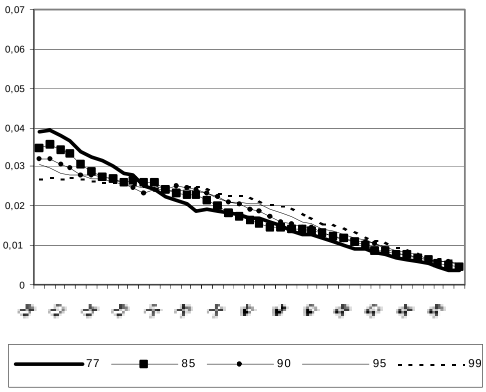


Figure 11
Age profile of 8 to 11 years of schooling - 1977 - 1999

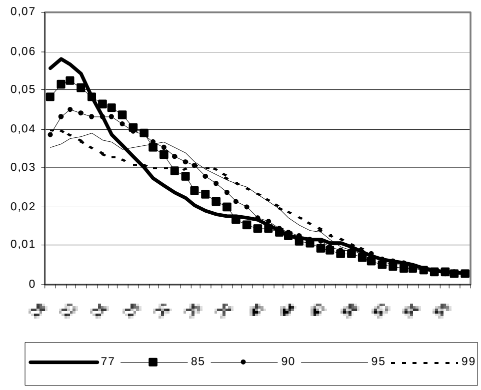
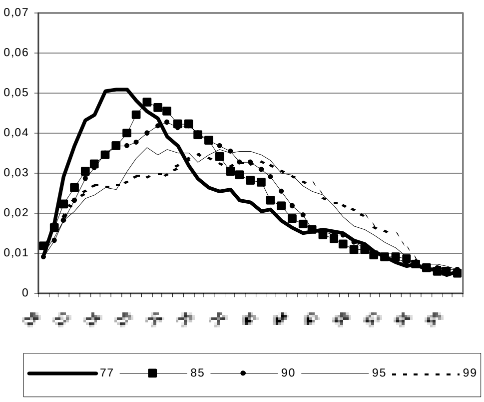


Figure 12
Age profile of 12 and more years of schooling - 1977-1999



As a result of both processes of aging and educational expansion, Figures 13 to 17 describe how the age structure of workers of all educational groups has became older through the years. However that aging effect is more impressive for the more educated groups (8 to 11 and 12+ years of schooling) since the share of younger workers (20-29 years) has sharply declined in these groups. Such evidence suggests that the educational gains in the period, especially within the range of 8 to 11 years of schooling, have add up to aging effect, enlarging the share of middle age workers (30 to 49 years of age) among those of middle level of schooling. In the following section we try to identify how both changes in the educational and age structures have affected the overall inequality in Brazil between 1977 and 1997.

Figure 13
Age Structure of Illiterates Over Time
1977-1999

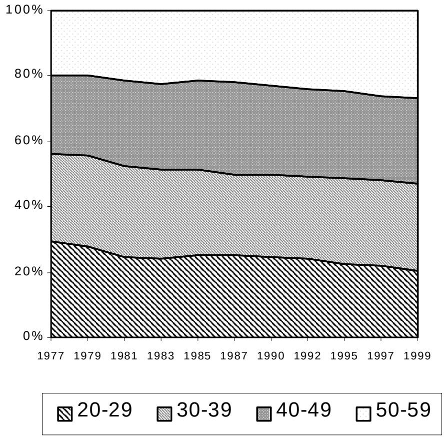


Figure 14: Age Structure of Workers with 1 to 3 Years of Schooling Over Time - 1977-1999

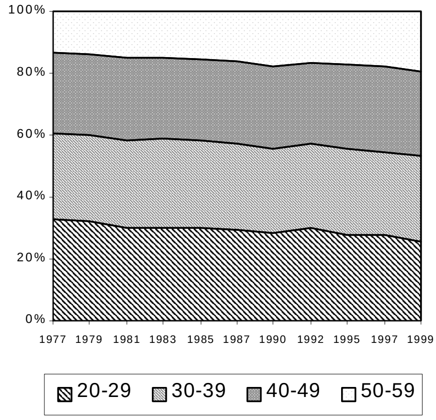


Figure 15: Age Structure of Workers with 4 to 7 Years of Schooling Over Time - 1977-1999

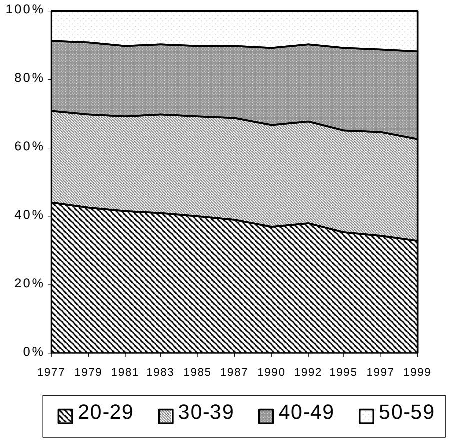


Figure 16: Age Structure of Workers with 8 to 11 Years of Schooling Over Time - 1977-1999

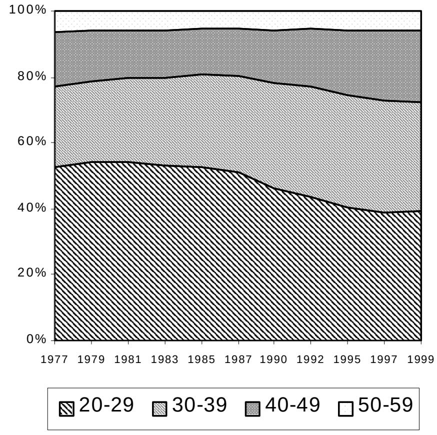
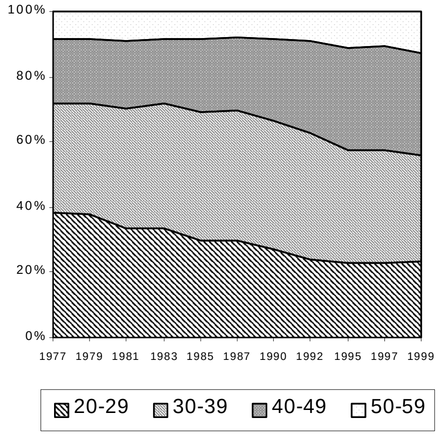


Figure 17: Age Structure of Workers with 12 and more Years of Schooling Over Time - 1977-1999



3) Econometric Methodology

The evolution of inequality over time can be described by a framework that includes time, work experience and cohort effects. Time (or macro) effects include changes in the economic environment, such as institutional factors, inflation and unemployment rates that affect the workforce as a whole. Experience effects capture, for example, the impact of a wage dispersion that is increasing over the life cycle together with an aging population. Cohort effects reflect permanent changes in the composition of the population due to differences in the characteristics of new entrants vis-à-vis retirees in the labor market (such as the size of the cohort and the level, quality and inequality of schooling).

Unfortunately, it is impossible to disentangle these effects due to a fundamental identification problem. As Heckman and Robb (1985) point out, birth cohort (c) is completely determined by age (a) and a time trend (t):

$$c = t - a \tag{3.1}$$

Following MaCurdy and Mroz (1995), we try to model the wage equation in a parsimonious way as a function of time, age and cohorts:

$$l(w) = \alpha + \mathrm{A}(a) + \mathrm{T}(t) + \mathrm{C}(c) + \mathrm{R}(a, t, c) + u \tag{3.2}$$

where the functions R are included to capture interactions between age, time and cohorts, like changing returns to experience over time. When exploring a fourth order polynomial on cohort, time, age and possible interactions between the three, we know that, because of the identification problem, only 14 linear combinations can be identified out of the 30 coefficients associated with fourth order terms. Therefore we chose the following equation to be taken to the data:

$$\begin{aligned} l(w) = \; & \alpha + \mathrm{A}_1 a + \mathrm{A}_2 a^2 + \mathrm{A}_3 a^3 + \mathrm{T}_1 t + \mathrm{T}_2 t^2 + \mathrm{T}_3 t^3 \\ & + \mathrm{R}_1 at + \mathrm{R}_2 at^2 + \mathrm{R}_3 a^2 t + u \end{aligned} \tag{3.3}$$

Hence, when interpreting the results of the regressions, it must be kept in mind that the cohort effects are present in the estimated coefficients. The error term in (3.3) include common time effects:

$$u = u_{it} + \bar{u}_t \qquad (3.4)$$

that are constructed to be orthogonal to the age and trend functions; that is, include no trends. All trends in the data will be reflected in the age and trend variables[6].

In the empirical investigation, we apply quantile regression techniques (Koenker and Basset, 1978). This allows us to model the evolution of the entire distribution of wages and not just the conditional mean. If all percentiles within a group evolve in the same way (apart form an intercept shift), then the changing dispersion of wages can be explained by changing prices and/or the composition of observed skill characteristics. Otherwise, unobserved effects are also important. The median defines the location of the distribution and the percentiles around it describe the changes in dispersion. We therefore have:

$$l(w)^q = \mathrm{A}^q(a) + \mathrm{T}^q(t) + \mathrm{R}^q(a, t) + u^q \qquad (3.5)$$

The set of functions $\mathrm{T}^q(t)$ for each quantile measures the trends in wages over time. Differences in these functions between the top and bottom of the distribution capture drifts on wage dispersion within-groups. Differences in the estimated coefficients across education groups, for the same quantile, measure changes in the returns to education over time, at specific points of the distribution. The functions $\mathrm{A}^q(a)$ measure the wage evolution as each education group gets older. Differences in the median age coefficient across education groups capture interactions between experience and education, whereas differences in the estimated age coefficients across quantiles suggest that the variance of wages increases with age, perhaps because of differential rates of learning by doing (see Gosling *et al*, 1999). Common macroeconomic shocks to the wage distribution are assumed to be the same for each educational group, regardless of age.

The empirical procedure is as follows: the raw data is split into education, year and age cells, using the fact that the variables of interest are all discrete, and we choose within each cell a population characteristic of interest. We then estimated it with the corresponding sample characteristic (using the weights provided by the household surveys). We estimate the 1st, 5th, 10th, 15th, 90th, 95th and 99th percentiles for each age, year and education cell. This is equivalent to using the full sample to regress each wage percentile on all possible education, year and age interactions. The percentiles are asymptotically normally distributed (see Koenker and Portnoy, 1998). The variance of each of these estimated order statistic (q) is given by:

$$V(q) = \frac{q(1-q)}{Nf(q)^2} \qquad (3.6)$$

We estimate f (q), the conditional density, using a Gaussian Kernel with bandwidth equal to half the standard deviation of wages for each cell.

---

[6] See MaCurdy and Mroz (1995).

We then try to impose some structure on the wage distribution by means of a minimum distance estimator. The minimum distance procedure chooses β such as to minimize

$$(\hat{q} - Z\beta)V(\hat{q})^{-1}(\hat{q} - Z\beta)$$

where $\hat{q}$ is the estimated order statistic and Z is a set of linear restrictions[7]. In our case, the restrictions imply that the age, trend and (orthogonal) time dummies can explain the behavior of each estimated order statistic across cells and over time. Imposing the restrictions means estimating weighted least squares regressions on the grouped data, for each quantile and education group separately. This procedure will give us consistent estimates of β[8]. Under the null hypothesis that the restrictions are valid, the minimized value follows a chi-squared distribution with degrees of freedom equal to the number of restrictions. All we have to do to construct the test statistic is sum the weighted square residuals; i.e., the empirical percentiles minus the age and trend effects, minus the orthogonal time effects.

4) Results

4.1) Effects of demographic and educational changes – 1977 to 1997

Tables 1 to 3 present the results of the median, 25th and 75th percentile regressions, respectively.

Table 1
Median Regression

Median Wages	Ed1	Ed2	Ed3	Ed4	Ed5
Trend	0.016	-0.163	-0.241	-0.043	-0.111
	0.003	*0.066*	*0.065*	*0.071*	*0.096*
Trend^2	-0.343	-0.259	-0.172	-0.313	-0.191
	0.003	*0.072*	*0.070*	*0.075*	*0.096*
Trend^3	0.161	0.156	0.142	0.16747	0.119
	0.001	*0.024*	*0.023*	*0.024*	*0.031*
Age	0.228	0.422	0.749	1.119	1.847
	0.001	*0.038*	*0.038*	*0.043*	*0.062*
Age^2	-0.043	-0.082	-0.202	-0.284	-0.612
	0.000	*0.020*	*0.021*	*0.024*	*0.032*
Age^3	0.001	0.001	0.013	0.021	0.066
	0.000	*0.003*	*0.003*	*0.004*	*0.005*
Trend*Age	0.011	0.056	0.014	-0.161	-0.170
	0.001	*0.031*	*0.033*	*0.039*	*0.050*
Trend*Age^2	-0.004	0.003	0.021	0.034	0.040
	0.000	*0.006*	*0.006*	*0.007*	*0.009*
Trend^2*Age	-0.001	-0.030	-0.046	-0.004	0.010
	0.000	*0.011*	*0.012*	*0.014*	*0.017*
χ^2 (861)	864.265	1065.034	1344.798	1109.501	1059.350
p-value	0,4623	0,000	0,000	0,000	0,000

Note: Standard errors in italics

[7] See Rothenberg (1972) and Chamberlain (1983).
[8] We estimate each quantile separately, which is not efficient but the procedure avoids measurement errors in a percentile to contaminate the estimation of other percentiles.

Table 2
25^{th} Quantile Regression

Median Wages	Ed1	Ed2	Ed3	Ed4	Ed5
Trend	0.346	0.012	-0.153	-0.081	0.011
	0.073	*0.064*	*0.062*	*0.072*	*0.103*
$Trend^2$	-0.782	-0.406	-0.318	-0.406	-0.360
	0.078	*0.070*	*0.067*	*0.075*	*0.105*
$Trend^3$	0.308	0.189	0.187	0.224	0.176
	0.026	*0.023*	*0.022*	*0.024*	*0.034*
Age	0.205	0.346	0.524	1.00	1.665
	0.042	*0.037*	*0.036*	*0.043*	*0.067*
Age^2	-0.034	-0.073	-0.110	-0.263	-0.525
	0.021	*0.019*	*0.020*	*0.024*	*0.035*
Age^3	-0.001	0.001	0.000	0.019	0.053
	0.003	*0.003*	*0.003*	*0.004*	*0.005*
Trend*Age	-0.005	-0.011	-0.007	-0.096	-0.135
	0.033	*0.030*	*0.031*	*0.039*	*0.054*
$Trend*Age^2$	-0.000	0.009	0.021	0.034	0.031
	0.006	*0.005*	*0.006*	*0.007*	*0.009*
$Trend^2*Age$	0.001	-0.013	-0.029	-0.036	0.000
	0.011	*0.011*	*0.012*	*0.014*	*0.019*
χ^2 (861)	1056.585	912.806	1248.574	1175.317	1141.411
p-value	0,000	0,1074	0,000	0,000	0,000

Note: Standard errors in italics

Table 3
75^{th} Quantile regression

Median Wages	Ed1	Ed2	Ed3	Ed4	Ed5
Trend	-0.114	-0.263	-0.192	0.051	-0.382
	0.069	*0.070*	*0.066*	*0.073*	*0.095*
$Trend^2$	-0.209	-0.075	-0.112	-0.308	0.161
	0.075	*0.075*	*0.071*	*0.076*	*0.094*
$Trend^3$	0.127	0.095	0.103	0.141	0.004
	0.025	*0.025*	*0.023*	*0.024*	*0.031*
Age	0.346	0.587	0.089	1.200	1.870
	0.039	*0.040*	*0.039*	*0.044*	*0.063*
Age^2	-0.076	-0.143	-0.214	-0.300	-0.628
	0.020	*0.021*	*0.022*	*0.025*	*0.032*
Age^3	0.004	0.009	0.014	0.023	0.068
	0.003	*0.003*	*0.003*	*0.004*	*0.005*
Trend*Age	0.072	0.067	-0.033	-0.229	-0.153
	0.032	*0.033*	*0.034*	*0.039*	*0.050*
$Trend*Age^2$	-0.013	0.002	0.025	0.036	0.042
	0.006	*0.006*	*0.006*	*0.007*	*0.009*
$Trend^2*Age$	-0.011	-0.037	-0.033	0.028	0.005
	0.011	*0.012*	*0.013*	*0.015*	*0.017*
χ^2 (861)	1179.842	1347.461	1479.89	1159.39	1071.064
p-value	0,000	0,000	0,000	0,000	0,000

Note: Standard errors in italics.

Inspection of the estimated coefficients in Table 1 reveals interesting features. First of all, there are meaningful differences in the estimated trend and experience effects across all the educational groups, revealing that returns to education were indeed changing in Brazil over the sample period and the returns to experience vary substantially across education levels. Additionally, the interactions between trend and age are significant, which could mean that returns to experience are changing over time and/or that cohort effects are important in Brazil.[9]

It is interesting to notice that the differences in the coefficients across education levels also hold true for the other quantiles, as shown in tables 2 and 3. Moreover, there are marked differences between the estimated parameters across percentiles for the same education level, which indicates that important changes in the wage distribution groups are taking place over time and over the life cycle in Brazil.

Fit of the Model

Besides the statistical tests, another procedure to evaluate the fit of the model is to compare the observed unconditional wage distribution with the one predicted by the restricted model. In order to construct the predicted wage distribution we proceed as in Gosling *et al* (2000). We first construct the conditional wage distribution, by choosing a fixed number w^q (within the observed unconditional sample wage distribution) and computing for each age / education / year cell (j):

$$\Pr(w < w^q \mid j) \qquad (4.1)$$

using the predicted wages. To construct the predicted wage distribution, we use the twenty predicted percentiles for each cell and a linear interpolation between them. We do so for a number of w^q's, until we have a rich description of the distribution. We then compute the unconditional distribution for each year:

$$q = \Pr(w < w^q) = \sum_j f_j \Pr(w < w^q \mid j) \qquad (4.2)$$

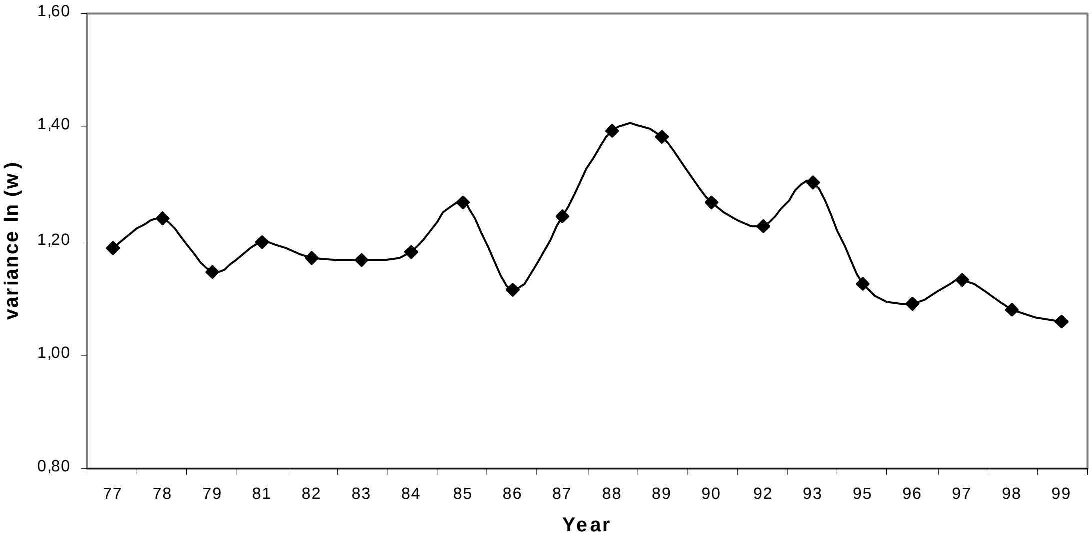
where f_j is the observed cell frequency in the population.

With the unconditional wage distribution we can compute any inequality measure we need. In this paper we chose to work with the variance of (log) wages which, besides being frequently used in the literature, is one of the decomposable measures of inequality. Figure 18 shows, firstly, that the wage dispersion has remained basically stable over the last two decades, despite the fact that this was a period of very volatile macroeconomic conditions, especially between 1986 and 1992 when inflation accelerated to unprecedented levels.

---

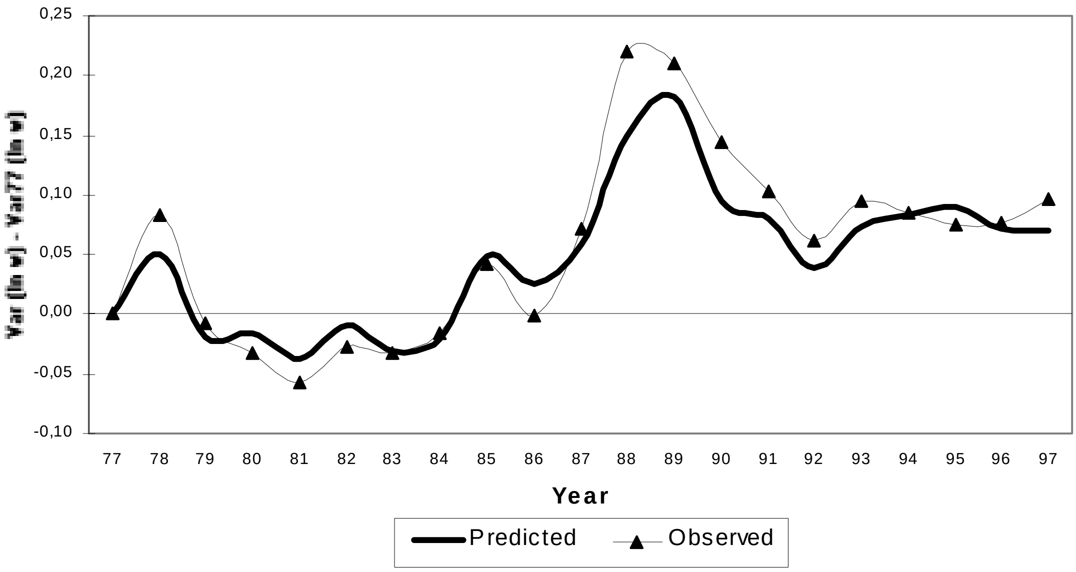
[9] For analysis of the role of cohort effects in the wage distribution, see MaCurdy, Mroz (1995) for US, Gosling et al (1999) for UK and Beaudry, Green (1997) for Canada.

Figure 18
Inequality - Variance of Log of Earnings



Wage dispersion over time, measured as changes from the variance of wages in 1977, is shown in Figure 19. The figure shows that the variance calculated from the restricted model closely mimics the behavior of the true variance, despite a period of short misalignment between 1989 and 1993. This means that we can use the predicted variance to construct counter-factual and describe, for example, how inequality would look like had the returns to education remained at the 1977 levels.

Figure 19
Fit of the Model - Changes to 1977



Counterfactual Analysis using Variance Decomposition

We now use the predicted wage distribution to perform the usual variance decomposition with log wages (*w*):

$$Var\ (w_t) = \sum_j f_{jt} Var\ (w_{jt}) + \sum_j f_{jt} \left[E(w_{jt}) - E(w_t)\right]^2 \qquad (4.3)$$

where:

$$Var\ (w_{jt}) = E(w_{jt}^2) - \left[E(w_{jt})\right]^2 \qquad (4.4)$$

$$E(w_{jt}) = \sum_q g(w^q \big| j,t) w^q \qquad (4.5)$$

$$E(w_t) = \sum_q g(w^q) w^q = \sum_q \left[\sum_j f_{jt} g(w^q \big| j,t) \right] w^q \qquad (4.6)$$

The empirical probability mass function g(w^q) was calculated using:

$$g(w^q) = G(w^q) - G(w^{q-\varepsilon}) \qquad (4.7)$$

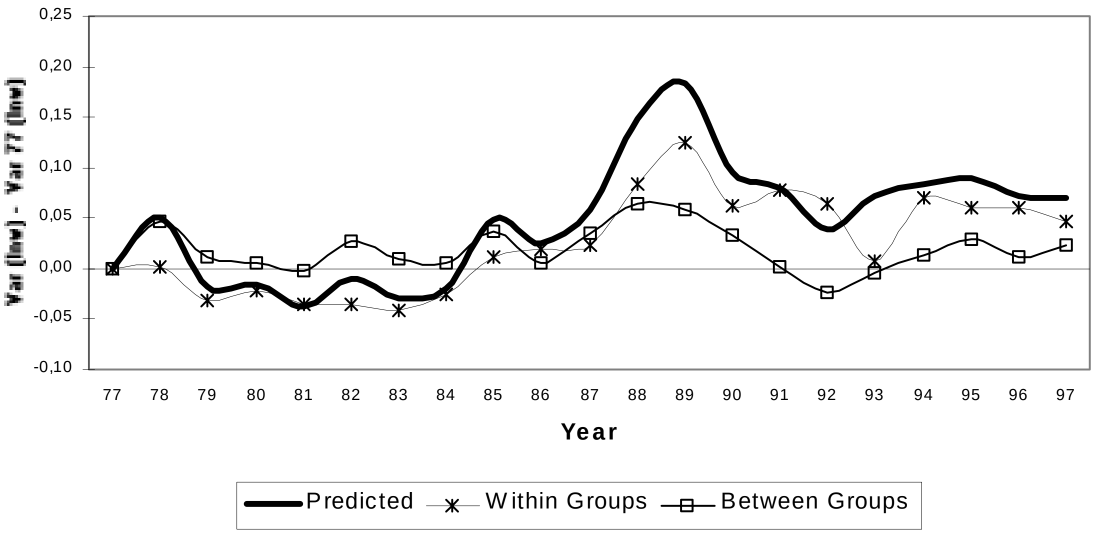
where:

$$G(w^q) = \Pr(w < w^q) = q$$

The first term on the right-hand-side of (4.3) refers to the within-groups dispersion and the second term deals with the dispersion between groups. Figure 20 depicts this variance decomposition analysis using our sample. It shows that the short-term behavior of the overall wage dispersion accompanied the dispersion within groups, while the behavior between groups remained basically stable throughout the sample period. In other words, the inequality of labor earnings in Brazil has risen slightly over the last two decades because of the dispersion within groups that contributed to a fall in inequality in the first part of the 1980s followed by a substantial rise in the 1990s. The pattern of within group inequality closely followed the behavior of the inflation rates in the period and may be related to staggered wage contracts in period of high inflation.

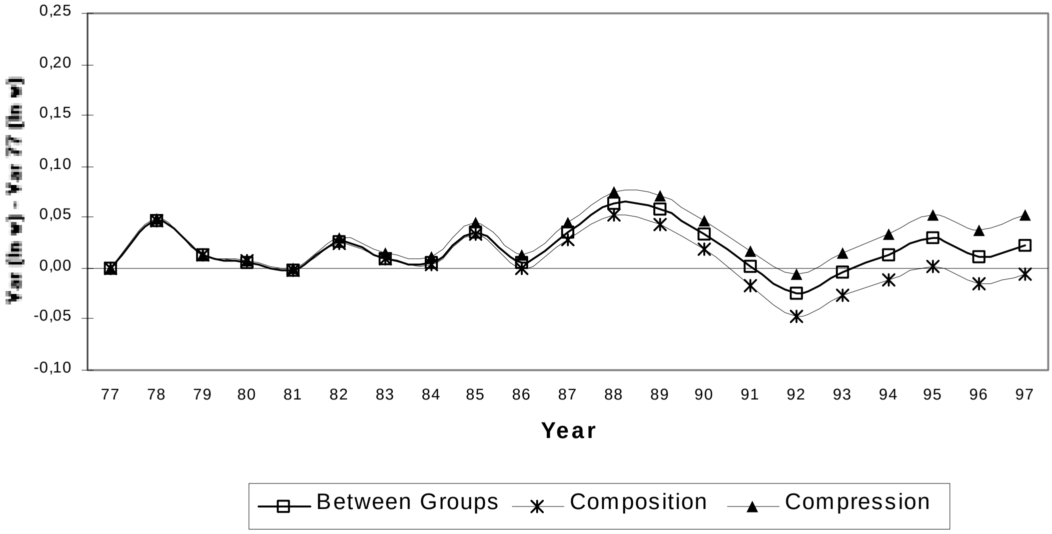
Figure 20

Variance Decomposition - Changes to 1977



Both the within group component and between-group components are affected by the composition of the labor force, as the presence of (f_{jt}) in equations (4.3) clearly implies. Besides, the evolution of the between-group contribution to inequality can be decomposed into a *composition effect* and a *compression effect*. The composition effect can be evaluated by maintaining the structure of the population constant at the 1977 level and allowing *prices* to change. The compress effect, on the other hand, can be measured by keeping prices at 1977 levels, while allowing the frequency weights (f_{jt}) to change. In order to capture the effects of age on the between-group component of inequality, we performed such counterfactual maintaining firstly only the age structure within each educational group, and next the returns to experience at the 1977 levels. As shown in Figure 21, the contribution of the age composition effect was to increase inequality, since the between group inequality would be lower had the age structure didn't change from 1977 to 1999. On the opposite side, the inequality would be higher if the returns to experience have remained at 1977 levels. It implies that returns to experience decreased in the period, probably as a result of the increasing supply of middle age workers.

Figure 21
Age Effects - Changes to 1977



4.2 Simulations on age and educational perspectives – 2000 to 2040

This subsection examines how the evolution of both the age and educational composition of the labor force is likely to affect inequality in the future. To do so, we perform a projection of the structure by age and education of the Brazilian labor force that will be between 20 and 60 years old in 2000, 2010, 2020, 2030 and 2040.

The population projection used in this simulation is presented in Sawyer et al. (1999). The next step was to project the male labor force participation rates specifics by age using the method proposed in Wajnman, Rios-Neto, (2001).Then, we projected the educational composition of the population using a method based on the observed experience of recent cohorts. We formulated two scenarios. In the first one, the *conservative* scenario, we assumed that there would not be meaningful educational gains from now on. In the second one, the *optimistic* scenario, we assumed a significant improvement in the Brazilian educational system. In this last scenario, after 2000, 100% of the population would have at least the lower primary education (4 years of schooling); 95% of those with the first grade would complete the upper primary and the high school education and 60% of those with high school grade would attend at least one year of college. It is important to notice that none of these scenarios should be considered realist, but as the bottom and the upper limits for our projections. Figures 22 and 23 present the educational distribution of labor force under the conservative and optimistic scenarios, respectively. It is clear that they are very different, especially regarding the share of the group with some college education (12 or more years of schooling) that reaches almost 50% by 2040 in the optimistic scenario, instead of 10% in the conservative one. Figures 1 to 10 in the appendix depict these distributions by age groups.

Figure 22
Projection of Educational Distribution of Labor Force under Conservative Scenario - 2000 - 2040

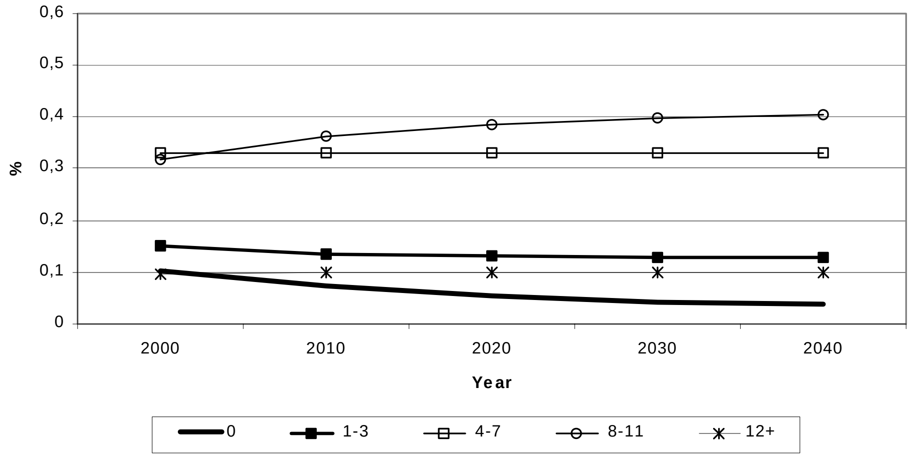
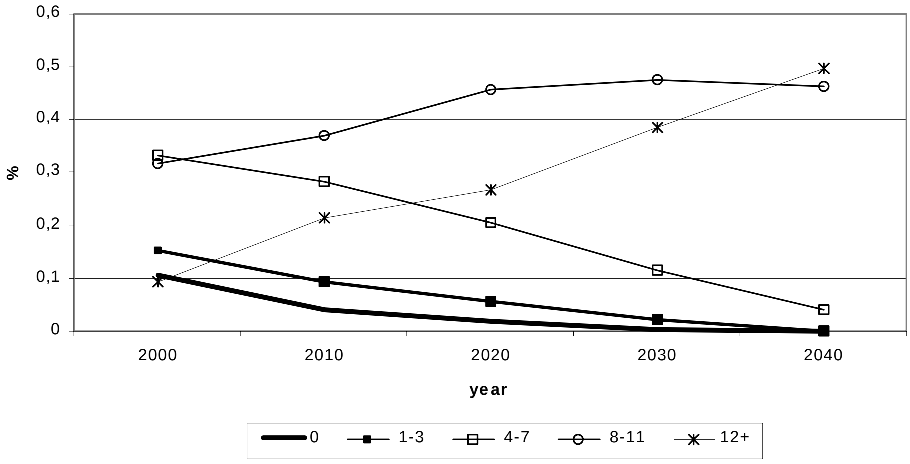


Figure 23
Projection of Educational Distribution of Labor Force under Optimistic Scenario - 2000 - 2040



Figures 24 and 25 show the relative position of the average wage of each educational group over the period under these two scenarios. We should emphasize that this exercise considers only the changes in the share of each educational group in the labor force without considering changes in the wages paid for these groups. Thus, the relative position of wages remains approximately constant in the conservative scenario. On the other hand, in the optimistic one, the average wages of the groups with 0, 1-3 and 4-7 years of schooling are getting far from the labor force average wage while the opposite is happening with those with 12 years of schooling. That is, as the labor force education rises continuously in the projected period, the overall mean wage of the labor gets closer to the wage of the more educated workers, due to the changes in the weights attributed to each educational group. As it will be showed, this evidence has a lot to do with the results presented in the next figures.

Figure 24
Difference from Average Wage by Educational Group
Under Conservative Scenario - 2000- 2040

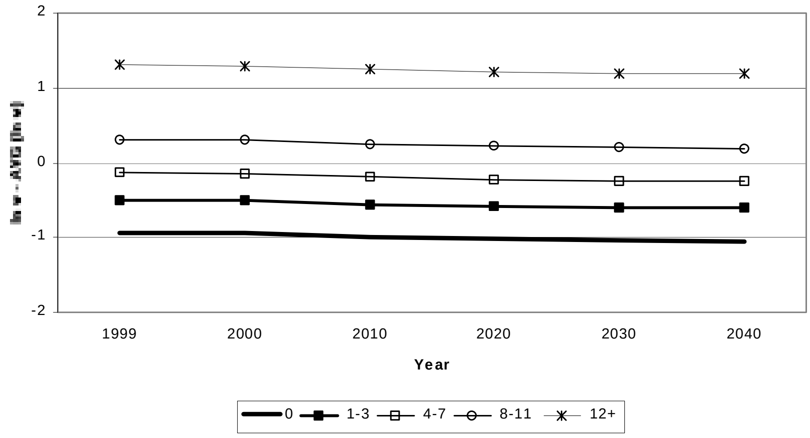


Figure 25
Differences from Average Wage by Educational Group
Under Optimistic Scenario - 2000- 2040

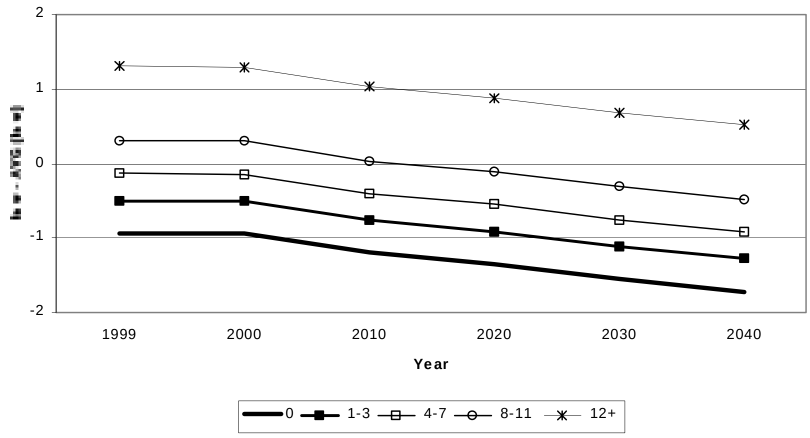
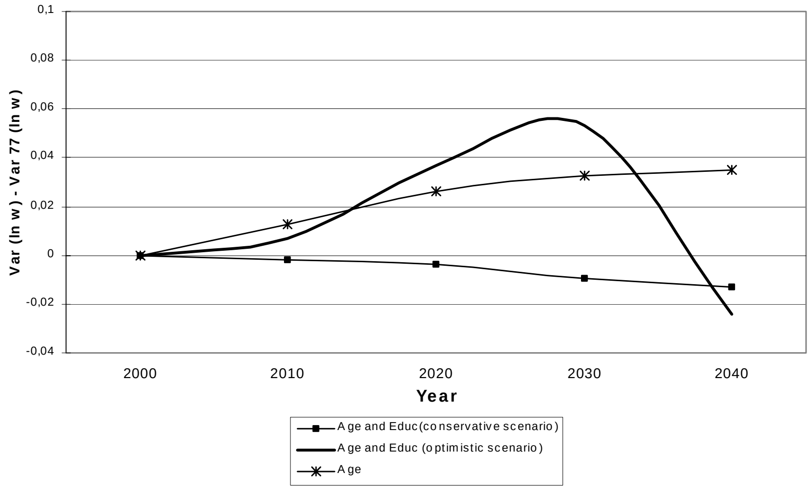


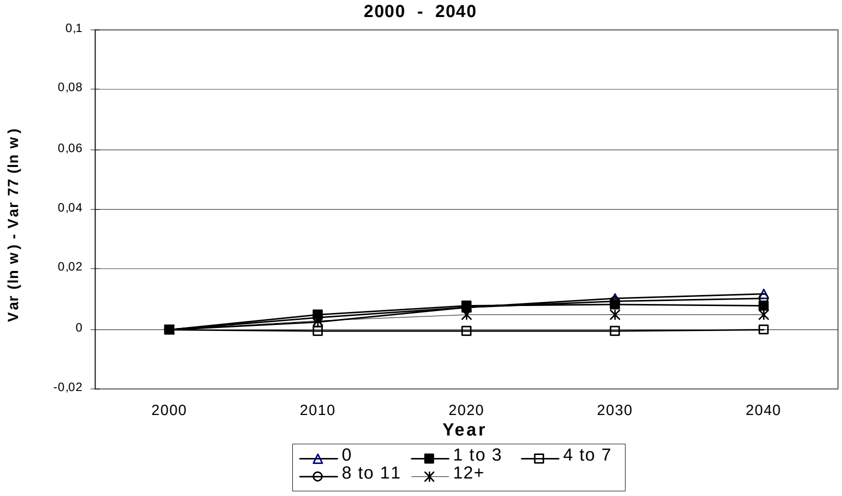
Figure 26 shows three kinds of composition effects projected over time. First, there is the age effect. According to this effect the overall inequality is predicted to increase over time through the population aging process. Actually, the literature has pointed exactly the opposite impact. However, as stressed by Lam (1989),the explanation for such result seems to be that the effect of labor force aging is not straightly predicted since middle age workers usually earn higher wages but the inequality between them tend to be the highest as well. Thus, the net effect of a larger share of older workers on the overall inequality should be empirically obtained and it depends on the sizes of the *between-component* impact (contributing to lower inequality) and the *within-component* impact (contributing to higher inequality).

Figure 26
Predicted Composition Effects OverTime
2000 - 2040



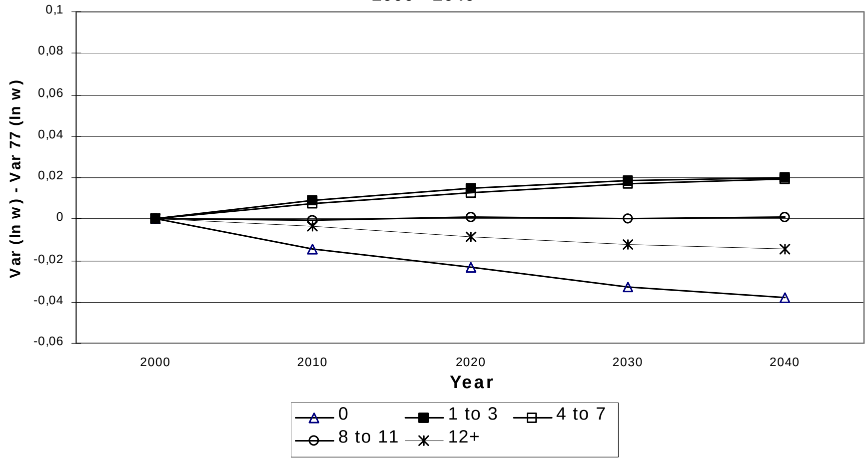
It is important to keep in mind that this age effect comprises the effect of age composition changes - predicted in the population projections - and also the effect of the aging of cohorts with the education levels achieved until 1999. So, this pure demographic effect implies some change in the age structure within each one of the educational groups. As shown in Figure 27, each group causes a different effect. Although all of them result in higher inequality, the effects of the groups with 4-7 and the 12 or more years of schooling are the lowest as their age composition are kept nearly constant over time (see figures 1 to 5 in the appendix).

Figure 27
Predicted Age Composition Effect by Educational Groups
2000 - 2040



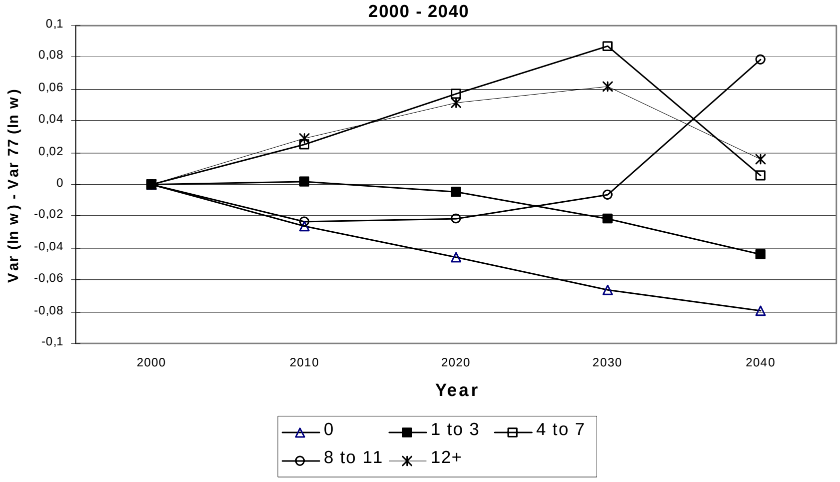
The second simulated effect is the combination of age and educational changes under the conservative scenario and it is shown in Figure 26. This effect tends to bring the overall inequality down at a slow pace, reducing less than 2% by 2040. Figure 28 simulates the contributions to this effect by each educational group. Both the first education group (illiterates) and the last one (at least some college) are contributing to reduce inequality in the future. In the case of the first group it is because its share in the labor force will decline, as pictured in Figure 22, but for the last group it is because the average labor force wage is getting closer to this group's wage, as pictures in Figure 24. On the other hand, the groups with 1-3 and 4-7 years of schooling will contribute to increase inequality as their wages are going away from the mean.

Figure 28
Predicted Age/Educational Composition Effect by Educational Groups
Conservative Scenario
2000 - 2040



The third effect depicted in Figure 26 is the simulation of age and educational structures under the optimistic scenario. In this case, the inequality is expected to rise strongly up to 2030 and start to fall quickly after that. Figure 29 simulates the contributions to this effect by each educational group. The results show again how the 'weight effect' (figure 23) and 'deviation from the mean effect' (figure 25) interact. Both, the first education group (illiterates) and the second one (1 to 3 years of schooling), are predicted to contribute to a decline in the overall inequality because, despite having wages further and further away from the mean, its importance will decline rapidly under the optimistic scenario. The third group (4-7 years of schooling) is predicted to foster inequality until 2030, due to the deviation from mean effect. Afterwards it will reduce inequality as its weight is predicted to be very small by 2040. The contribution of the workers with 8 to 11 years of schooling to higher inequality is expected to be strong after 2030 since its wage will distance from the mean and its share will reach almost 50% of the labor force in 2040. Finally, the college group (12+) is predicted to increase inequality until 2030 since its average wage is higher than the overall labor force average wage. However, as this group will be the majority by 2040, its wage will get closer to the mean, thus changing its effect to inequality. It is clear that, as the old cohorts leave the labor market and the new cohorts get more and more educated, this group tends to define the mean wage of the labor force, driving inequality down.

Figure 29
Predicted Age/Educational Composition Effect by Educational Groups
Optimistic Scenario
2000 - 2040



5) Conclusions

In this paper we investigated the behavior of the distribution of wages of Brazilian males from 1977 to 1997. The results showed that the behavior of the overall inequality accompanied the dispersion within groups, while the behavior of the between groups remained basically constant through the period. Counterfactual exercises applied to this period have shown that the contribution of the age structure changes was to increase inequality, while the returns to experience contributed to decrease it. The simulation exercise using the predicted evolution of the age structure and education levels of the labor force from 2000 to 2040 indicated that inequality tends to decrease but the pattern of this change will heavily depend on the pace of the expansion the education gains. We should point out that one of the drawbacks of the present simulations is that they do not take into account the possibility of interactions between the composition and the compression effects; i.e., that the evolution of the returns to education over time may diminish the impact of the 'deviation from mean effect'.

These exercises demonstrated that the overall inequality tends to decrease as a result of the aging of the labor force and the improvement of the education processes. What is pointed out clearly is that these processes may result in a time when there will be a small fraction of workers with very low levels of education, thus with its wages very far from the mean, contributing to keep inequality in a very high level. The year of 2030 in our simulations under the optimistic scenario represents this moment. On the other hand, 2040 represents the overcome of these picture, as this group of unskilled workers are almost completely out of labor force.

6) References

Barros, R., Henriques, R. and Mendonça, R., "Education and Equitable Economic Development" , *Economia*, 1 (2000), 111-144.

Beaudry, P. and Green, D., "Cohort Patterns in Canadian Earnings: Assessing the Role of Skil Premia in Inequality Trends", NBER Working Paper 163 (1997).

Chamberlain, G. "Quantile regressions, censoring and the structure of wages", in Christopher Sims (ed) *Advances in Econometrics*. Proceedings of the 6th World Congress in Barcelona, 1 (1993).

Chiswick, B. "Earnings Inequality and Economic Development", *Quarterly Journal of Economics*, 85 (1971), 21-39.

Easterlin, R., Schaaeefeer, C., Macunovich, D.1993. Will the baby boomers be less well off than their parents? Income, wealth and family circumstances over the life cycle in the United States. *Population and development Review*, 19, n.3, Sept., 497-522.

Gosling, A, Machin, S. and Meghir, C., "The Changing Distribution of Male Wages in the UK", Centre for Economic Performance Discussion Paper 271 (1999).

Higgins, M., Williamson, J. 1999. Explaining inequality the world round: cohort size, Kuznets curves and openness. *NBER Working Paper* n. 7224, July.

Heckman, J. and Robb, R., "Using Longitudinal Data to Estimate Age, Period and Cohort Effects in Earnings Equations", in Feinberg and Mason (eds), *Analysing Longitudinal Data for Age, Period and Cohort Effects* (New York: Academic Press, 1985)

Knight, J. and Salbot, R. "Education Expansion and the Kuznets Effect", *American Economic Review* 73 (1983), 1132-1136.

Koenker, R. and Portnoy, "Quantile Regressions" University of Illinoy Discussion Paper (1998).

Kuznets, S., "Economic Growth and Income Inequality", *American Economic Review* 45 (1955) 1-28.

MaCurdy, T. and Mroz, T., "Estimating Macro Effects from Repeated Cross-Sections", University of Standford Discussion Paper (1995)

Menezes-Filho, N., Fernandes, R., Picchetti, P. 2001. Rising human capital but constant inequality: the education composition effect in Brazil. University of São Paulo, Feb. (mimeo).

Sawyer O. D.; Wong, L.R., Carvalho J.A. M., Fígoli, M., Andrade F.C.D., Barbieri A. F. e Tavares C.R.G. (1999). Projeção Populacional, por Sexo e Grupos Qüinqüenais, das Unidades da Federação, Brasil, 1990-2020. Belo Horizonte: CEDEPLAR-UFMG. (Not published).

Wajnman, S. Rios-Neto, E. 2001. Women's participation in the labor market in Brazil: elements for projecting levels and trends. *Brazilian Journal of Population Studies*, v.2.

7) Appendix

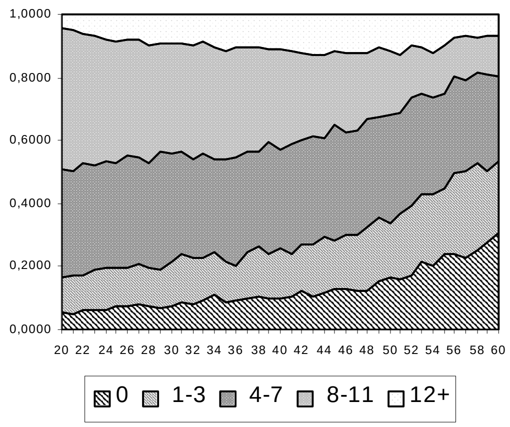


Figure 1
Educational Structure of Labor Force by Age under Conservative Scenario
2000

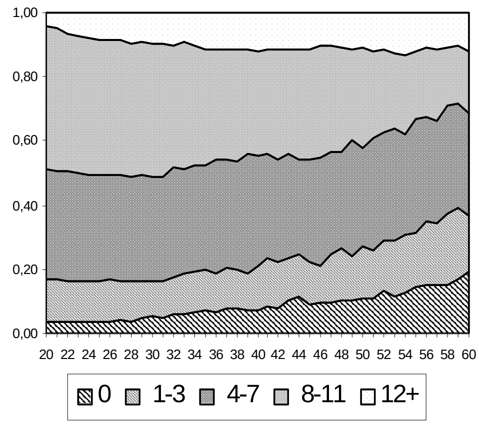


Figure 2
Educational Structure of Labor Force by Age under Conservative Scenario
2010

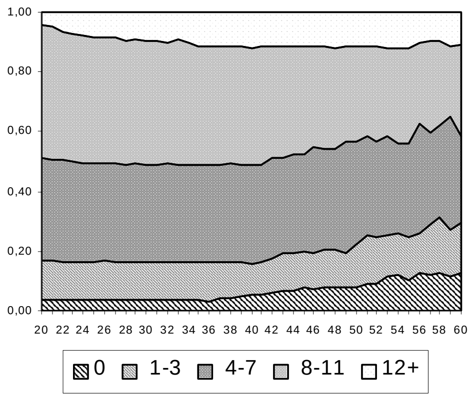


Figure 3
Educational Structure of Labor Force by Age under Conservative Scenario
2020

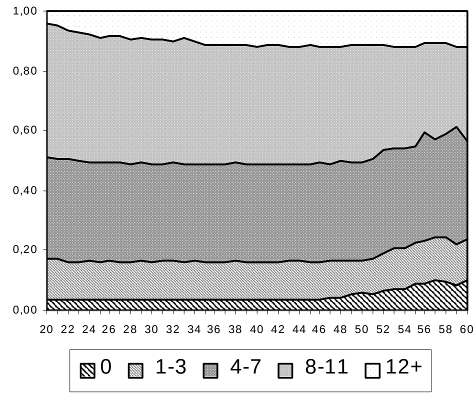


Figure 4
Educational Structure of Labor Force by Age under Conservative Scenario
2030

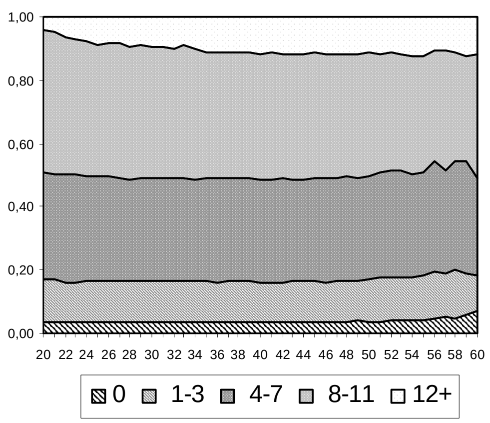


Figure 5
Educational Structure of Labor Force by Age under Conservative Scenario
2040

Figure 1
Labor Force Structure by Educational Groups over Time - 1977-1999

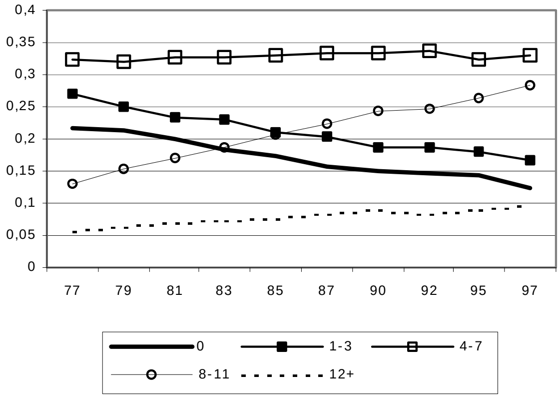


Figure 2
Proportion of Illiterates in the Labor Force in each Age Group
1977-1999

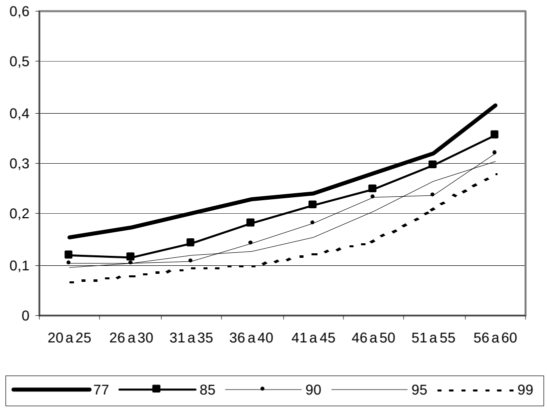


Figure 3
Proportion of Workers with 1 to 3 Years of Schooling in each Age Group
1977-1999

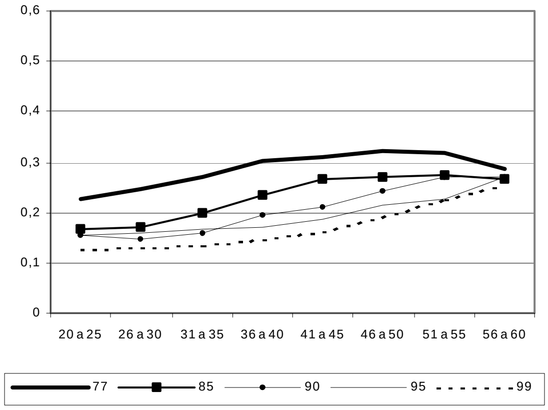


Figure 4
Proportion of Workers with 4 to 7 Years of Schooling in each Age Group
1977-1999

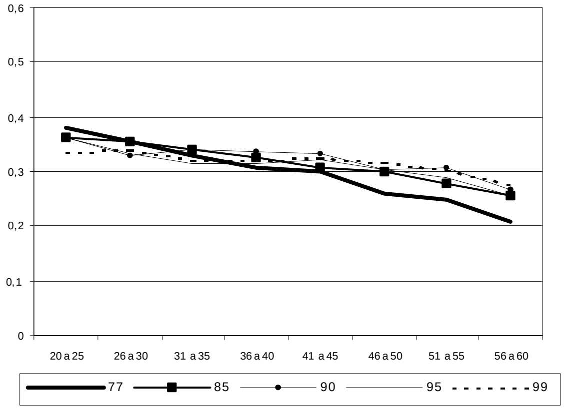


Figure 5
Proportion of Workers with 8 to 11 Years of Schooling in each Age Group
1977-1999

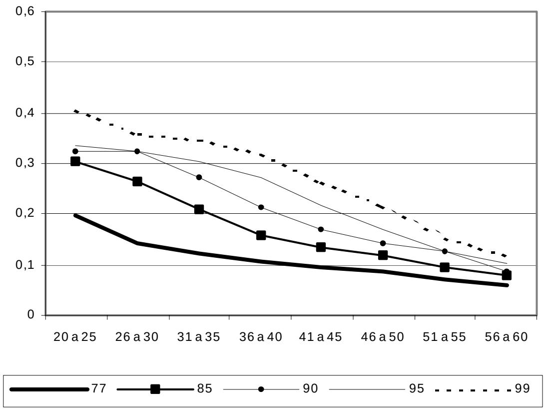


Figure 6
Proportion of Workers with 12 or more Years of Schooling in each Age Group
1977-1999