Evolution of Earnings and Rates of Returns to Education in Mexico

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Abstract

This paper reviews the factors and mechanisms that have been driving inequality in Mexico and finds that educational inequality accounts for by far the largest share of Mexico's variation in earnings inequality. The contribution of inequality of education to inequality of earnings in Mexico is the second highest in Latin America, after Brazil, and the significance of education has been increasing over time. Moreover, the income effect is always prevalent, and the distribution of education is highly significant even after controlling for changes in other relevant variables, such as age, economic sector, region, and labor market status. The increase in earnings inequality, however, does not appear to be the result of a worsening in the distribution of education, although the income profile, which is related to the returns to schooling, has become much steeper. This means that the shift in demand toward high-skilled labor has not been matched by an increase in supply. The probable reason is that the Mexican economy's increased openness has facilitated the transmission of skill-biased technological change.

Key words: Economic Development, Salary Wage Differentials, Rate of Return

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Achieving sustainable economic growth with a more egalitarian distribution of income is at the core of Mexico's development challenge. Yet the country does not perform well in terms of equity when compared with other Latin American countries. According to a recent study developed by the Inter-American Development Bank (IDB, 1998-1999), Mexico has the sixth most unequal distribution of overall household income in Latin America (and the third worst in urban areas). In the broader international context, Mexico's ratio of income share accruing to the top 10 percent of the population to the share accruing to the bottom 40 percent is higher than what is observed both for the high-income countries and for the vast majority of low-income countries (see table 3A.3).

The second half of the 1980s and the 1990s were an especially meaningful period for the Mexican economy, which sought to move from a protected economy driven by the public sector to a globally integrated economy driven by the private sector. This structural change resulted in sizable economic growth, but Mexico's income distribution became increasingly unequal and failed to respond either to economic growth or to public policy.

Most remarkable, the level, deterioration, and resistance to policy of Mexico's inequality over the past decade coexisted with very rapid progress in educational attainment, both in terms of coverage and distribution of schooling (De la Torre 1997). This phenomenon, which has been observed in other developing countries as well as developed ones, is somewhat surprising, given the powerful equalizing properties generally attributed to education.

This paper reviews the factors and mechanisms driving inequality in Mexico. More specifically, it examines the expansion in earnings inequality with emphasis on the role of education,[2] establishes an analytical framework that permits analysis of the interaction between

2. Wages are related directly to individual characteristics and do not depend on family structure. Besides, the

education and the labor market, and examines the evolution of earnings inequality in light of the macroeconomic and educational policies followed in the 1980s and 1990s.

The paper is organized as follows. Section I describes the evolution of total current income inequality, using information contained in the National Household Income and Expenditures Survey (ENIGH) and using household income per capita as the unit of analysis. Section II focuses on the evolution of individual earnings inequality, using information in the National Urban Employment Survey (ENEU). Section III investigates how much of Mexico's earnings inequality can be explained by educational inequality, as well as other control variables, both in gross and marginal terms.[3] Section IV analyzes the evolution of educational attainment. Section V relates changes in the distribution of education to changes in earnings inequality. Section VI examines the evolution and structure of the rates of returns to education by means of ordinary least squares and quantile regressions. The last section offers concluding remarks.

I. The Evolution of Total Income Inequality

The evaluation of income inequality in Mexico is based on information available in the ENIGH (see annex 1 for a brief description). This survey captures total current income of households, including non-monetary income, earnings, and other sources of monetary income. The unit of analysis is the household, and the concept of income is household income per capita.[4]

The main results of this evaluation are shown in table 1, which indicates a sizable deterioration in income distribution during the period under review. While the poorest 20 percent

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distribution of wages explains much of the distribution of welfare in society.

3. Educational attainment has an impact not only on income but also on other outcomes that are important for an individual's well-being but are not necessarily measured in monetary terms. This study, however, does not consider the non-monetary impacts of education.

4. Total current income of the household divided by the number of household members. That is, we are considering the household as a unit characterized by a flow of income transfers and disregarding aspects related to equivalence scale.

of the population lost almost one-seventh of their income share (0.6 percentage point), the richest 10 percent increased theirs by something close to one-seventh (5.2 percentage points). Moreover, the richest group was the only one to gain over that period, as not only the poorest but also those in the middle lost in relative terms.

Table 1. Lorenz Curves for Total Current Income, 1984–96

(accumulated income share; percent)

Population share	*1984*	*1989*	*1992*	*1994*	*1996*
10	1.66	1.39	1.32	1.39	1.39
20	4.47	3.88	3.68	3.76	3.89
30	8.19	7.29	6.92	6.98	7.29
40	12.85	11.65	11.09	11.08	11.63
50	18.76	17.05	16.26	16.28	17.08
60	26.15	23.78	22.83	22.79	23.86
70	35.51	32.25	31.13	31.10	32.39
80	47.64	43.12	42.14	41.93	43.44
90	64.53	58.75	58.32	57.68	59.33
92	68.79	63.06	62.81	62.03	63.61
94	73.73	68.03	68.03	67.26	68.68
96	79.38	73.82	74.47	73.70	74.95
98	86.68	81.60	82.81	82.49	83.32
100	100.0	100.0	100.0	100.0	100.0
Bottom 20 percent	4.5	3.9	3.7	3.8	3.9
Middle 40 percent	21.7	19.9	19.2	19.0	20.0
Middle-high 30 percent	38.4	35.0	35.5	34.9	35.5
Top 10 percent	35.5	41.3	41.7	42.3	40.7
Gini coefficient	0.473	0.519	0.529	0.530	0.515
Theil T index	0.411	0.566	0.550	0.558	0.524

Note: Total current income is based on household income per capita.

Source: Author's calculations based on ENIGH.

Mexico in the period from 1984 to 1996 was marked by a series of regressive income transfers from almost the entire spectrum of the population to the richest stratum. Accordingly, the most commonly used inequality index points to a worsening in income inequality over this span of time. The Gini coefficient, which is especially sensitive to changes in the middle of the distribution, rose from 0.473 in 1984 to 0.515 in 1996. The Theil T index, which is extremely sensitive to changes in the upper and lower tails, rose from 0.411 in 1984 to 0.524 in 1996.

The worsening of income distribution is indisputable, but two points must be stressed. The first one is that, according to the ENIGH survey, most of the deterioration occurred in the middle to late 1980s (1984–89). There was little variation in earnings inequality in the early 1990s, except for a slight trend toward deterioration. From 1989 to 1994, the income share accruing to the 20 percent poorest decreased slightly (from 3.9 to 3.8 percent), whereas the share accruing to the richest 10 percent increased (by 1 percentage point); those in the middle also experienced losses.

The second fact is surprising and hard to explain: income distribution improved between 1994 and 1996, an interval of time in which the Mexican economy experienced a severe financial crisis.[5] Usually one would expect inequality to rise during times of recession, because the rich have more ways of protecting their assets than the poor. This is especially true of labor, which is basically the only asset of the poor (the labor-hoarding hypothesis). Nevertheless, during this time the 10 percent richest experienced relative losses (their income share dropped 1.6 percentage points), and inequality declined. The Gini coefficient dropped from 0.534 0.530 in 1994 to 0.515 in 1996, while the Theil T index dropped from 0.558 to 0.524. It could be argued that the richest experienced severe capital losses that affected their total income more than the poor, but this hypothesis is not supported by the data presented in table 2: monetary income other than wages and salaries as well as financial income increased as a share of total income in that

5. In 1994, the current account deficit was $30 billion, about 7 percent of gross domestic product (GDP). The main effects of the financial crisis were (a) GDP and domestic demand fell 6.2 and 14 percent, respectively; (b) the unemployment rate rose from 3.7 percent in 1994 to 6.2 percent in 1995; and (c) GDP per capita decreased 7.8 percent and workers experienced a significant reduction in their real wages, nearly 17 percent in 1995.

time period, particularly in urban areas. Therefore, the fall in inequality remains somewhat puzzling.

Table 2. Share of Total Income by Source and Geographic Location, 1994 and 1996

(percent)

	1994			*1996*		
Source	*Total*	*Urban*	*Rural*	*Total*	*Urban*	*Rural*
Monetary current income						
Total labor earnings	47.12	49.01	32.07	44.51	46.08	33.75
Property (business) income	16.96	16.23	22.75	17.74	17.11	22.07
Property income and rents	1.10	1.13	0.87	1.35	1.47	0.51
Income from cooperative firms	0.22	0.24	0.12	0.06	0.03	0.32
Monetary transfers	5.44	4.72	11.23	6.55	5.89	11.11
Other current income	0.64	0.67	0.36	0.69	0.66	0.91
No monetary current income						
Self-consumption	1.44	0.81	6.46	1.20	0.69	4.72
Nonmonetary payment	1.55	1.58	1.28	2.25	2.32	1.82
Gifts	5.04	4.73	7.57	6.07	5.86	7.55
Housing imputed rent	16.02	16.60	11.39	13.76	14.28	10.20
Financial income	4.46	4.28	5.91	5.80	5.62	7.04

Source: Author's calculations based on ENIGH.

Table 3 displays the Gini coefficient and Theil T index for urban and rural areas using total current income. For both indexes inequality was lower in rural areas than in urban areas and was remarkably stable until 1992. After a small decrease in 1994, rural inequality increased in 1996, contrary to the aggregate result. In light of these outcomes, the behavior of current income distribution in Mexico seems to be driven by the trends in urban areas.

Table 3. Inequality Measures for Total Current Income, 1994–96

	Gini coefficient			*Theil T index*		
Year	*National*	*Urban*	*Rural*	*National*	*Urban*	*Rural*
1984	0.473	0.442	0.448	0.411	0.356	0.375
1989	0.519	0.498	0.444	0.566	0.526	0.361
1992	0.529	0.498	0.434	0.550	0.483	0.353
1994	0.534	0.508	0.419	0.558	0.499	0.325
1996	0.519	0.493	0.452	0.524	0.470	0.390

Source: Author's calculations based on ENIGH.

II. THE EVOLUTION OF EARNINGS INEQUALITY

How much of total income inequality is due to earnings inequality? Table 4 presents the results of total current income inequality for each of its components: earnings,[6] monetary income excluding earnings, and nonmonetary income by urban and rural areas[7] Earnings contribute to most of the overall inequality, being responsible for almost half of inequality at the national level. These figures clearly may be affected by the underreporting of capital gains, but understanding the mechanisms that produce earnings inequality represents a large step toward understanding the behavior of total inequality. As long as labor is the main, if not the only, asset of the poor, a better knowledge of earnings inequality is a valuable input for the assessment of poverty and welfare issues.

6. Earnings as defined in the ENIGH survey include salaries and wages, paid over-time, tips, contract workers' earnings, Christmas or New Year bonuses and other gifts, and other monetary compensations (nonregular earnings). Earnings as defined in the ENEU survey include salaries and wages, self-employed workers' earnings, contract workers' earnings, and implicit salaries of firm owners, as well as nonmonetary earnings.

7. Although the results are shown for the Gini coefficient, these also could have been obtained for the Theil T index, as both of them satisfy the six propositions listed in Shorrocks (1980 and 1984) as well as Shorrocks and Mookherjee (1982).

Table 4. Decomposition of Total Current Income, 1984–96

(percentage share in overall Gini)

Region and year	*Earnings*	*Monetary income excluding earnings*	*No monetary current income*	*Total*
National				
1984	46.0	32.9	21.0	100.0
1989	41.0	36.0	23.0	100.0
1992	42.9	31.9	25.2	100.0
1994	50.2	25.9	23.9	100.0
1996	46.7	29.4	23.9	100.0
Urban				
1984	45.6	32.2	22.2	100.0
1989	38.6	37.3	24.1	100.0
1992	41.4	33.1	25.5	100.0
1994	50.0	26.0	24.0	100.0
1996	46.1	29.8	24.1	100.0
Rural				
1984	30.7	49.5	19.8	100.0
1989	35.7	43.5	20.8	100.0
1992	29.6	42.2	28.2	100.0
1994	31.9	43.8	24.2	100.0
1996	35.7	41.2	23.1	100.0
1996	35.7	41.2	23.1	100.0

Source: Author's calculations based on ENIGH.

We use the ENEU household survey to examine the behavior of earnings inequality because it is extremely rich in household characteristics (see annex 2).[8] Table 5 shows that the distribution of earnings has become more unequal in recent times. The Gini coefficient jumped from 0.395 in 1988 to 0.442 in 1997, after reaching a peak of 0.464 in 1996. Similarly, the Theil T index increased from 0.327 in 1988 to 0.372 in 1997, with 0.474 in 1996. Another index, the $R_{10/20}$, which is the ratio of the income share accruing to the richest 10 percent to that accruing to the poorest 20 percent, increased from 4.48 to 6.04 over the period, reaching a maximum of 6.74 in 1996.

8. In order to reduce the heterogeneity of the sample and also aspects related to self-selection, the population under analysis includes individuals living in urban areas, between 16 and 65 years old, and working 20 hours a week or more. It does not include seasonal workers. Also the two highest observations were dropped from the sample given the clear evidence of outliers in some years.

Table 5. Inequality Indexes for the Distribution of Earnings, 1988–97

(percent)

Population share	*1988*	*1989*	*1990*	*1991*	*1992*	*1993*	*1994*	*1995*	*1996*	*1997*
Bottom 20 percent	7.54	7.62	7.19	6.84	6.47	6.13	5.98	5.91	5.72	5.95
Middle 40 percent	25.23	24.45	23.86	23.41	23.37	22.86	22.36	22.59	22.09	23.01
Middle-high 30 percent	33.44	34.15	33.96	33.77	33.52	33.37	32.94	33.42	33.61	35.13
Top 10 percent	33.78	33.78	34.98	35.98	36.64	37.63	38.72	38.08	38.58	35.91
Gini coefficient	0.395	0.398	0.414	0.426	0.434	0.447	0.458	0.455	0.464	0.442
Theil T index	0.327	0.328	0.350	0.380	0.396	0.414	0.470	0.427	0.474	0.372
$R_{10/20}$	4.48	4.43	4.87	5.26	5.66	6.14	6.47	6.44	6.74	6.04

Source: Author's calculations based on ENEU (third quarter).

There are two main differences in the pattern shown by the distribution of earnings and total current income. First, the gains were not limited to the richest 10 percent. Those in the seven-, eight-, and nine-tenths of the distribution also improved their relative earnings over the period by almost 2 percentage points; the biggest losers were the middle 40 percent, who lost more than 2 percentage points of their income share. Second, the earnings distribution clearly worsened in the 1990s up through 1996, although the inequality associated with total current income was moderately stable in the 1990s and even improved in 1996.

The behavior of total current income inequality and earnings inequality from 1994 to 1996 supports the idea that the poor, who rely mostly on labor as a source of income, are the least able to protect themselves during a recession. However, the substantial drop in earnings inequality from 1996 to 1997 is, once more, a surprising finding. For example, the $R_{10/20}$ index declined from 6.74 in 1996 to 6.04 in 1997. It is true that the Mexican economy as a whole had a strong and impressive performance in 1997. The aggregate growth rate was around 7 percent, real investment grew 24 percent, exports grew 17 percent, industrial production increased 9.7 percent, and the civil construction sector, which is highly intensive in less-skilled labor, grew close to 11 percent. Under such a scenario, an improvement in the distribution of earnings is not unlikely, but the magnitude and quickness of the recovery call for a detailed inspection of the mechanisms responsible for it.

Three broad hypotheses frequently are advanced to explain the earnings inequality experienced in Mexico and other countries.[9] These link the increase in earnings inequality to (a) increased openness of the economy, (b) institutional changes in the labor market, and (c) skill-biased technological change.

The first of these hypotheses argues that as trade barriers are reduced, an economy is placed under heightened competitive pressure to specialize along its lines of comparative advantage. A developed country with a relatively abundant supply of high-skilled workers, like the United States, will be induced to specialize in activities that require a high level of skill or education as its low-skilled industries come under increased competitive pressure from countries with an abundant supply of low-skilled, low-wage workers.

Hanson and Harrison (1995) examine the impact of Mexican trade reform on the structure of wages using information at the firm level. They test whether trade reform shifted employment toward industries that are relatively intensive in the use of skilled labor (the Stolper–Samuelson-Type [SST] effect). They conclude that the wage gap was associated with changes within industries and firms, which cannot be explained by the SST effect. Thus the increase in wage inequality was due to other factors.[10] Hanson (1997) examines a trade theory based on increasing returns, which has important implications for regional economies, and concludes that employment and wage patterns are consistent with the idea that access to markets is important for the location of industry.

9. See, for example, the "Symposium on Wage Inequality" (1997) and the "Symposium on How International Exchange, Technology, and Institutions Affect Workers" (1997).
10. The Stolper-Samuelson effect also is examined under NAFTA in Burfisher and others (1993).

This first hypothesis has several problems when applied to the United States and becomes even less persuasive when applied to Mexico. Mexico greatly liberalized its trade regime after 1984. However, the reduction of its trade barriers was mostly with respect to imports from the developed countries, notably the United States and Canada, whose share of total Mexican merchandise imports increased from 68 percent in 1985, to 73 percent in 1993, and to almost 78 percent in 1996. Since Mexico has an abundant supply of low-skilled labor compared with its northern neighbors, the liberalization of trade could be expected to induce a pattern of specialization that would raise the relative demand (and hence wages) of the lesser-educated members of the labor force. This did not happen. Instead, the increase in earnings inequality observed in Mexico followed the same pattern as that observed in the United States: less-educated workers experienced real wage declines, while highly educated workers experienced real wage improvements. The trade-based explanation may still be relevant, however, to the extent that greater openness facilitates the transfer of ideas and technology. This is a more persuasive explanation of the increase in earnings inequality. A variant of the globalization-technology nexus advanced by Feenstra and Hanson (1996) involves outsourcing in which multinational enterprises in the developed country relocate their less skill-intensive activities to the less skill-abundant developed countries. However, what is referred to as a low-skill activity in the United States may be a high-skill activity in Mexico, which could explain the similarity in the evolution of earnings inequality in both countries.

The second explanation revolves around institutional changes such as reductions in the minimum wage, the weakening of trade unions, and the decline of state-owned enterprises. The existence of a binding minimum wage, for example, truncates the lower end of the wage distribution. As the minimum wage is allowed to erode—say, through inflation—it becomes less binding by moving farther down the low end of the wage distribution, with the result that, ceteris paribus, a higher share of wages will lie below the previous minimum-wage level. This translates into an increased dispersion in wages and earnings. Institutional developments have not exerted a significant influence on the earnings distribution since the early 1980s (see Hernández, Garro, and Llamas 1997). The distribution of real wages, for example, does not reveal any significant distortions around the minimum wage, which suggests that it is not a binding constraint. The fact that this minimum wage has continued to erode in real value, therefore, seems to be irrelevant. Similarly, the distribution of union wages is not significantly different from the distribution of nonunion wages, once differences in educational levels are taken into account. This also renders any erosion of union power irrelevant for the distribution of earnings. In conclusion, although the influence of institutional factors cannot be rejected entirely, it does not appear to be the principal cause of the increase in earnings inequality.

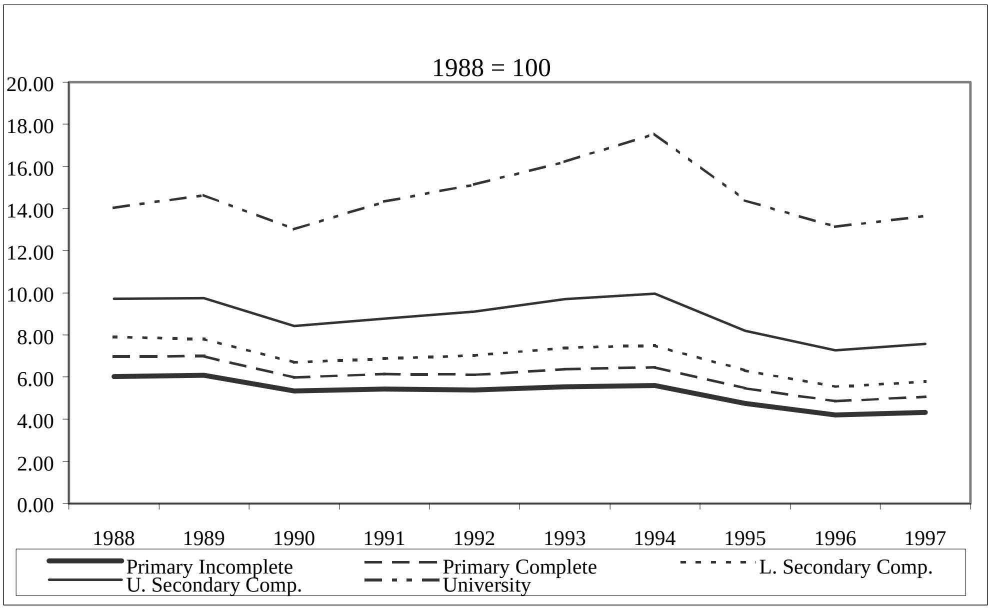
A persuasive explanation, both for the United States and for Mexico, seems to be one that links earnings inequality to skill-biased technological changes that raise the relative demand for higher-skilled labor. Cragg and Epelbaum (1996) examine the shift in demand in Mexico. They point out that the major source of rising inequality is a biased shift in demand rather than a uniform growth in demand when there are different labor supply elasticities. Meza (1999) also investigates shifts in demand and offers the hypothesis that the shift in demand toward a more educated labor force "within" an economic sector explains the increase in their premium when compared with the shift in demand for less-educated workers "between" economic sectors. Tan and Batra (2000) study the skill-biased technical change hypothesis as a plausible explanation of wage inequality using data at the firm level for Colombia, Mexico, and Taiwan (China). They obtain the following results: (a) a firm's investments in technology have the largest impact on the distribution of wages for skilled workers, (b) they have the smallest impact on wages paid to unskilled workers, and (c) wage premiums paid to skilled workers are led primarily by the firm's investments in research and development (R&D) and training. Such conclusions seem to support the skill-biased technological change hypothesis.[11] According to the typology used by Johnson (1997), the type of technological change that drives wages up for the more highly skilled workers and drives wages down for the less-skilled workers (as occurred in both the United States and Mexico) is extensive skill-biased technological change. Under this type of technological change, skilled workers are more efficient in jobs that were traditionally performed by unskilled workers.

As shown in figure 1, all series have the same trend for all periods.[12] However, beginning in 1990 conditional real earnings for workers with a university education increased substantially, while conditional real earnings for workers with low levels of education remained steady up to 1994. After that, earnings differentials among workers of all educational levels remained constant. This suggests that factors other than the supply of new workers with a basic education drove earnings differentials by level of schooling.

11. These results should be considered carefully, since the analysis is based on data at the firm level and only for the manufacturing industry.

12. Median real hourly earnings are estimated using quantile regression models ($\theta = 0.5$) and conditioned on experience, gender, labor market status, economic sector, and region (see annex 1 for definitions).

Figure 1. Conditional Median Real Hourly Earnings by Educational Level, 1988–97



Note: Medians were calculated conditional on experience, experience squared, gender, economic sector, labor market status, and region.

Source: Author's estimations based on ENEU survey.

In sum, demand and supply, interacting within a context of economic modernization and globalization, generate the trend toward greater wage disparity. However, none of these explanations deals explicitly with changes in the distribution of education or with the interaction between the educational policies that induced them and the workings of the labor market.

III. Static Decomposition

This section aims to evaluate the contribution to earnings inequality in Mexico of a set of variables, related either to individual attributes, such as schooling and age, or to form of participation in the labor market, such as number of hours worked or status, for selected years from 1988 to 1997. The idea is to measure the inequality that is left unexplained after taking into account the differences in average earnings among workers in different groups. When the exercise is conducted for a single variable, this reduction is said to be the gross contribution of the variable to overall wage inequality. When a variable is added to a model that contains all the remaining variables, the change in the gross contribution of these two models is called the marginal contribution of the added variable. In other words, the gross contribution is the uncontrolled explanatory power of a given variable, and the marginal contribution is its explanatory power controlled by a set of other seemingly relevant variables.

Short Review

Before proceeding to the decomposition exercise, it is worth reviewing the conclusions of other recent studies on the evolution of earnings inequality and some variables that are important in the process of earnings formation.

Cragg and Epelbaum (1996) show that both average wage and education skill premium defined as the percentage increase in wages over those of the group with primary schooling have increased substantially for workers with more education. In other words, the higher is the level of education, the larger is the increase in average wages, which in turn leads to an increase in inequality. They also examine whether the high demand for skilled labor is industry specific, task specific, or simply the result of general education. In order to assess the marginal contribution of other factors that are not related to education, these factors are controlled by a set of dummy variables that describe the industry- and task-specific effects. The authors conclude that the industry-specific effect is small and that the task-specific effect (occupation variable) explains half of the growth in wage dispersion from 1987 to 1993. This conclusion may not be correct, however, as occupation might be considered an endogenous variable, which is determined by education. As shown on table 3A.2, educational level and occupation variables are highly correlated. In contrast, the correlation between education and other variables is low. Hence the occupation variable should be handled carefully in any kind of analysis.

Methodology

The approach in this study uses inequality measures known as "generalized entropy indexes." Bourguinon (1979), Cowell (1980), and Shorrocks (1980, 1984) have shown that such measures alone satisfy all the desirable properties for any inequality measure and are additive decomposable.[13]

Assume that the population is divided into g groups (according to education, for instance). Then a measure of inequality is said to be additive decomposable (see Shorrocks 1980) when it can be written as:

$$(1) \qquad I = I(\beta_g, \alpha_g, I_g) = I_B(\beta_g, \alpha_g) + \sum_g w(\beta_g, \alpha_g) I_g$$

where β_g is the fraction of the labor force employed in group g, α_g is its relative mean income, and I_g represents the wage dispersion within this group as measured by the index *I*.

The term I_B on the right side of equation 1 corresponds to the inequality *between* groups (that is, the amount of inequality that would be observed in the case of an earnings redistribution within each group, in such a way that, at the end, all workers in a group would receive the same earnings). The second term in the right-hand side (I_W) reflects the inequality *within* groups; that is, the share of overall inequality associated with factors other than those involved in the particular partition under study. It represents the degree of inequality that would be observed if all groups had the same average earnings. Notice that I_W is a weighted average of the internal

13. Annex 2 reviews several methods of decomposition analysis.

inequalities, the weights, $w(\beta_g, \alpha_g)$, being a function of the population share and average earnings of each group.

One thus can estimate the contribution of a given variable(s) to the overall earnings inequality at a given point in time as the fraction of this inequality that would be eliminated if the average wage of all groups formed by that (those) variable(s) were equalized, while keeping the internal dispersions unchanged. The *rationale* behind this exercise is that the effect of this (these) variable(s) is (are) captured by differences in average earnings at the group level.

Among the most commonly used inequality indexes, the Theil T is one of the few that is additive decomposable.[14] The general statistics needed for the decomposition by age, sector, level of schooling, hours worked, and status from 1988 to 1997 are shown in table 6.

14. For the decomposition of the Theil T, see Ramos (1990) and annex 2.

Table 6. General Statistics for the Static Decomposition, 1988–97

	1988			*1992*			*1996*			*1997*		
Variable	*Beta*	*Alfa*	*Theil*	*Beta*	*Alfa*	*Theil*	*Beta*	*Alfa*	*Theil*	*Beta*	*Alfa*	*Theil*
Schooling												
Primary incomplete	0.185	0.70	0.220	0.147	0.65	0.234	0.129	0.57	0.283	0.127	0.57	0.207
Primary complete	0.277	0.81	0.257	0.259	0.72	0.207	0.244	0.65	0.270	0.237	0.67	0.207
Lower secondary complete	0.241	0.88	0.228	0.264	0.80	0.281	0.257	0.74	0.264	0.263	0.76	0.229
Upper secondary complete	0.189	1.09	0.234	0.205	1.07	0.300	0.216	1.04	0.278	0.221	1.05	0.259
University complete	0.107	2.10	0.343	0.124	2.32	0.359	0.154	2.30	0.430	0.151	2.22	0.289
Total			0.327			0.395			0.464			0.372
Age												
16–25	0.320	0.74	0.202	0.323	0.68	0.201	0.280	0.64	0.239	0.282	0.66	0.217
26–34	0.278	1.07	0.259	0.276	1.07	0.334	0.279	1.02	0.332	0.274	1.05	0.320
35–49	0.282	1.17	0.364	0.293	1.24	0.441	0.323	1.26	0.541	0.327	1.21	0.374
50–65	0.119	1.13	0.475	0.108	1.14	0.521	0.119	1.08	0.589	0.117	1.13	0.496
Total			0.327			0.395			0.464			0.372
Sector												
Primary sector	0.019	0.99	0.508	0.016	0.99	0.667	0.014	1.20	0.976	0.012	1.20	0.621
Manufacturing industry	0.274	0.97	0.323	0.242	0.96	0.379	0.221	0.94	0.559	0.227	0.92	0.371
Nonmanufacturing industry	0.058	0.91	0.224	0.064	1.06	0.409	0.060	0.91	0.382	0.057	0.88	0.331
Commerce	0.178	1.01	0.415	0.196	0.92	0.415	0.188	0.90	0.484	0.180	0.89	0.407
Finance services or rent	0.030	1.39	0.230	0.027	1.77	0.384	0.024	1.90	0.407	0.027	1.79	0.332
Transportation or communications	0.066	1.12	0.191	0.069	1.12	0.310	0.064	1.03	0.344	0.068	1.06	0.255
Social services	0.253	1.10	0.280	0.261	1.12	0.380	0.294	1.23	0.373	0.293	1.25	0.317
Other services	0.122	0.73	0.385	0.125	0.70	0.291	0.136	0.58	0.274	0.136	0.58	0.269
Total			0.327			0.395			0.464			0.372
Hours worked												
20–39	0.201	0.89	0.278	0.174	0.87	0.391	0.174	0.84	0.399	0.172	0.86	0.333
40–48	0.581	0.96	0.280	0.566	0.95	0.332	0.525	0.96	0.421	0.540	0.98	0.331
49+	0.218	1.20	0.438	0.260	1.20	0.483	0.301	1.16	0.535	0.288	1.13	0.444
Total			0.327			0.395			0.464			0.372
Status												
Employer	0.046	2.32	0.549	0.048	2.44	0.463	0.048	2.18	0.561	0.046	2.15	0.428
Self-employed	0.158	0.97	0.338	0.149	0.89	0.354	0.174	0.75	0.377	0.167	0.79	0.340
Informal salaried	0.122	0.58	0.210	0.140	0.54	0.158	0.147	0.47	0.174	0.150	0.48	0.175
Formal salaried	0.609	0.99	0.240	0.602	1.03	0.342	0.558	1.14	0.412	0.567	1.13	0.311
Contract	0.064	0.98	0.230	0.062	0.96	0.297	0.072	0.77	0.302	0.070	0.79	0.268
Total			0.327			0.395			0.464			0.372

Note: The sample includes only those who reported information on level of education, age, economic sector, and labor market status simultaneously.

Source: Author’s calculations based on the ENEU (third quarter).

Results

The results for the exercise of static decomposition are shown on table 7.[15] Education (the result of the interaction between demand and supply) is the variable that accounts for by far the largest share of earnings inequality in Mexico, in terms of both gross and marginal contributions. The gross contribution—that is, the variable's explanatory power when it is considered alone—amounted to one-fifth of total inequality in 1988 and one-third in 1997.[16] The marginal contribution—that is, the increase in the explanatory power when the variable is added to a model that already has the other variables—was remarkably stable and meaningful, staying around 21 percent throughout the period. The difference between the two contributions has been growing over time, indicating that the degree of correlation with other variables has been increasing. This means that the "indirect" effects are becoming more important.

Table 7. Contribution to the Explanation of Earnings Inequality, 1988–97

(percent)

	1988		*1992*		*1996*		*1997*	
Variable	*Gross*	*Marginal*	*Gross*	*Marginal*	*Gross*	*Marginal*	*Gross*	*Marginal*
Education	20.2	20.8	26.9	21.6	29.3	21.2	32.6	21.2
Age	5.4	8.3	7.2	6.1	6.6	6.2	7.3	5.4
Economic sector	2.3	8.1	4.0	5.2	6.8	5.2	8.6	4.4
Status	12.8	11.2	13.7	8.9	13.7	7.4	15.6	7.5

Source: Author's calculations based on ENEU.

The other variables considered seem to be much less important. All three of them—but particularly economic sector and status in the labor market—display an upward trend in their gross contribution and a declining trend in their marginal contribution. This can be interpreted as

15. Since this exercise is very intensive in the number of observations (which constitutes its main handicap), the variable "hours worked" was dropped in order to avoid the problem of having cells with too few observations. The decision was made through the comparison among different combinations of variables, where hours worked ended up being the least relevant.

16. In most earnings equations for any country, the set of measurable observable variables explains at most 60 percent of the total variance. In the United States, education accounts for 10 percent of the total variance.

evidence that the interaction between these variables and education has become more intense. That is, the workers' skills are becoming increasingly more relevant to the determination of their type of participation in the labor market as well as to their position across different economic segments of the economy. The same pattern holds when number of hours worked instead of sector is considered (see table 8).

Table 8. Contribution to the Explanation of Earnings Inequality, 1988–97

(percent)

	1988		*1992*		*1996*		*1997*	
Variable	*Gross*	*Marginal*	*Gross*	*Marginal*	*Gross*	*Marginal*	*Gross*	*Marginal*
Education	20.2	20.2	26.9	22.3	29.3	22.6	32.6	24.5
Age	5.4	5.4	7.2	4.8	6.6	4.6	7.3	4.5
Hours worked	1.7	3.8	1.9	3.3	1.3	4.0	1.2	3.5
Status	12.8	7.6	13.7	7.1	13.7	6.0	15.6	6.5

Source: Author's calculations based on the ENEU (third quarter).

The analysis of these results leads to the conclusion that educational inequality is a key variable for understanding earnings inequality in Mexico.[17] Though remarkable to some extent, this finding comes as no surprise in the Latin American context. The results for some countries in the region, where similar exercises have been conducted, are reported in table 9. Mexico stays in the average range for Latin American countries and displays a situation close to that observed in Colombia and Peru. However, education seems to be more important for inequality in Brazil and much less important in Argentina and Uruguay. This is a comparison in relative terms. Given that in Colombia and Peru, where education has a similar explanatory power, there is a lower degree of inequality than in Mexico, the absolute contribution of education is higher in

17. Additional evidence is that the explanatory power of the complete model was 42.5 percent in 1988, 45.0 percent in 1992, 45.5 in 1996, and 48.3 percent in 1997. This means that the marginal contribution of education was almost equal to the joint contribution of age, economic sector, and status in the labor market. Székely (1995) applies the static decomposition of the Theil to the ENIGH for the years 1984, 1989, and 1992, using education, occupation, region, economic sector, and job status as control variables. The main finding is that this set of variables explains 55, 58, and 64 percent of income dispersion, respectively, for each year, with education and job status being the relevant variables.

Mexico. In absolute terms, the contribution of education to inequality in Mexico is the second highest in Latin America, after Brazil. Moreover, what seems to be particularly interesting in the Mexican experience is the fact that the significance of education has been increasing over time. Therefore, the evolution of educational distribution and the income profile associated with it, as well the link between changes in this distribution and changes in earnings inequality, are addressed in the next section.

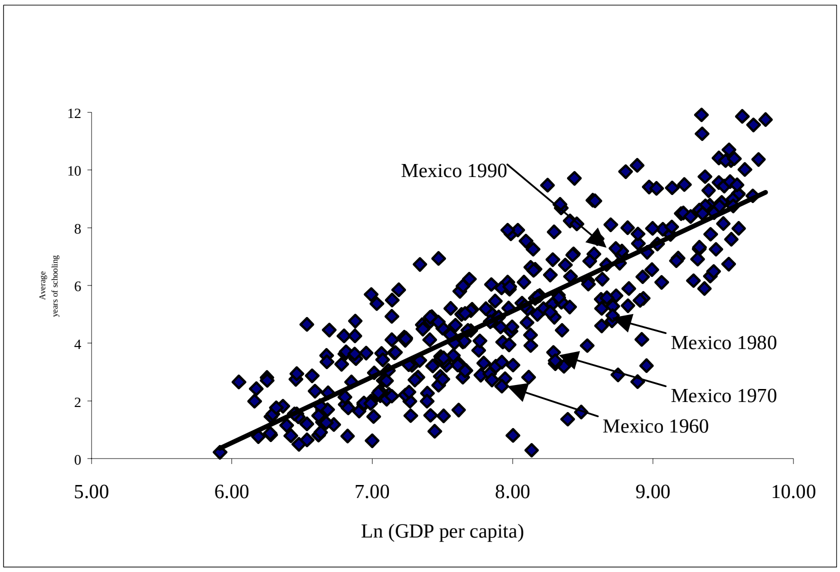
Table 9. Contribution of Education to Earnings Inequality: International Comparison

Country	*Author(s) and reference*	*Period*	*Gross contribution (period)*
Latin America	Altimir and Piñera (1982)	1966–74	17–38
Argentina	Fiszbein (1991)	1974–88	16–24
Brazil	Ramos and Trindade (1991)	1977–89	30–36
	Vieira (1998)	1992–96	30–35
Colombia	Reyes (1988)	1976–86	29–35
	Moreno (1989)	1976–88	26–35
Costa Rica	Psacharapoulos and others (1992)	1981–89	23–26
Peru	Rodríguez (1991)	1970–84	21–34
Uruguay	Psacharapoulos and others (1992)	1981–89	10–13
Venezuela	Psacharapoulos and others (1992)	1981–89	23–26

IV. The Evolution of Educational Attainment

Levels of educational attainment have increased rapidly in most developing countries since the 1950s (Schultz 1988). Although Mexico also partook of that development, there was a significant lag in its educational indicators. Londoño (1996), for example, points to an "education deficit," according to which Latin American countries in general, and Mexico in particular, have approximately two years less education than would be expected for their level of development. Elías (1992) finds that education was the most important source of improvement in the quality of labor in Latin America between 1950 and 1970, although such improvements did not take place to the same extent in Mexico as in other countries in the region. This changed dramatically in the 1980s. Figure 2 shows that, although Mexico's educational attainment increased steadily after the 1970s, it remained below the international trend line.[18] In the 1980s, however, the growth of educational attainment in Mexico accelerated, permitting it to catch up with international standards by 1990, where its placement in figure 2 is slightly above the trend line.

Figure 2. Cross-Country Relation between Educational Attainment and GDP, 1960–90



The closure of Mexico's education gap vis-à-vis the rest of the world was hastened in part by the country's economic stagnation. Mexico's real GDP per capita in the mid-1990s was roughly the same as it had been in the first half of the 1980s. Nevertheless, this should not detract

18. The scatter diagram is based on 317 observations from five years. The trend line represents the least squares regression line given by

S = -13.17 + 2.28 Ln*(GDPcap)* Adjusted R^2 = 0.68.

(-18.7) (26.0) *t*-values in parentheses

The application of Ramsey's RESET test to this regression equation failed to detect a specification error; unlike with the alternative specification of the following type: $S = a + bX + cX2$.

from the remarkable increase in schooling that occurred during the 1980s. While the level of average schooling in Mexico increased by roughly a year per decade during 1960–80 (from 2.76 to 4.77 years), it increased by two years in the decade of the 1980s. This acceleration in schooling was the product of concerted efforts to increase the coverage of basic education, combined with advances made in the reduction of primary school repetition and dropout rates.

The observations pertaining to Mexico, ordered by date, are shown in table 10.

Table 10. Years of Schooling and Gross Domestic Product per Capita in Mexico, 1960–90

Year	*Average schooling (years)*	*Ln (GDP per capita in 1980 U.S. dollars)*
1960	2.76	7.95
1970	3.68	8.29
1980	4.77	8.71
1985	5.20	8.63
1990	6.72	8.67

Source: Author's calculations based on Barro and Lee data set. The World Bank

With respect to changes in the distribution of schooling by socioeconomic groups, there are several aspects to be considered. In particular, three are examined here: the changes in this distribution that are related to gender, economic sector, and age.

Table 11 shows the distribution of schooling by gender from 1988 to 1997. Even though there were clear improvements for both males and females, which signify an upgrade of educational attainment, women achieved a better performance during that period, especially at the top of the distribution. Improvements for males, in contrast, were spread more evenly over the entire distribution. Nevertheless, in 1997 women were undoubtedly more educated than men, as their cumulative distribution dominated that of men (see figure 3).[19]

19. This is true for the overall distribution in 1997 relative to that in 1988.

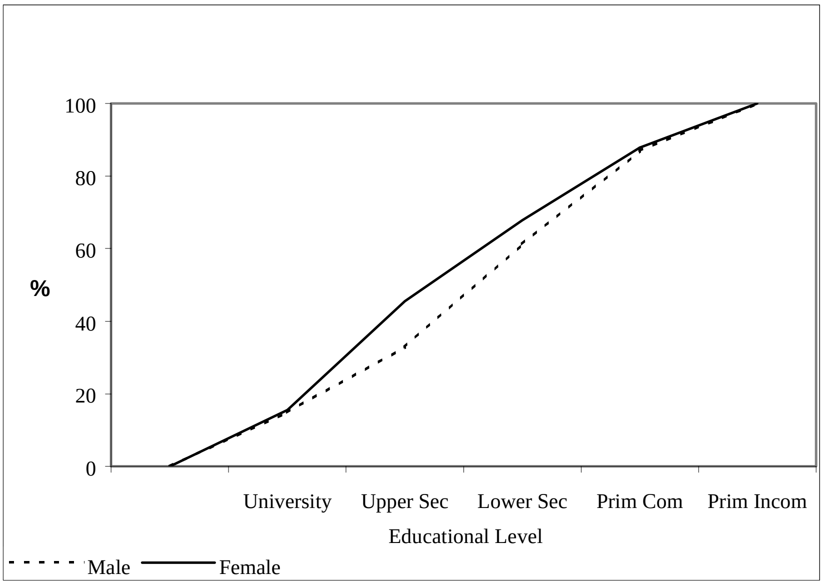
Table 11. Educational Distribution by Gender, 1988 and 1997

(percent)

Educational group	*Primary incomplete*	*Primary complete*	*Lower secondary complete*	*Upper secondary complete*	*University complete*
1988					
Male	19.0	30.1	24.5	14.6	11.8
Female	17.3	22.2	23.2	29.1	8.2
Total	18.5	27.7	24.1	18.9	10.7
1997					
Male	13.0	25.7	28.4	18.0	14.9
Female	12.2	20.0	22.3	30.1	15.5
Total	12.7	23.7	26.3	22.1	15.1

Source: Author's calculations based on the ENEU survey (third quarter).

Figure 3. Cumulative Educational Distribution by Gender, 1997



Source: Author's calculations based on ENEU data.

With respect to the distribution of schooling by economic sector, table 12 shows a significant upgrade from 1988 to 1997. Three points, nonetheless, deserve to be stressed. First, financial and social services industries became relatively more intensive in the use of high-skilled labor. Second, the primary sector, together with nonmanufacturing industry and other services, were characterized by more intensive use of low-skilled labor. Third, in a surprising way, the manufacturing industry, in contrast to the common wisdom, cannot be characterized as a sector that intensively uses high-skilled labor.

Table 12. Educational Distribution by Economic Sector, 1988 and 1997

(percent)

Educational group and year	*Primary incomplete*	*Primary complete*	*Lower secondary complete*	*Upper secondary complete*	*University complete*
1988					
Primary sector	41.1	21.0	13.3	14.3	10.3
Manufacturing industry	16.2	33.3	27.8	14.7	8.0
Nonmanufacturing industry	36.6	28.5	14.7	9.0	11.2
Commerce	18.0	28.7	28.8	18.7	5.8
Finance services or rent	4.8	6.1	19.5	47.1	22.5
Transportation or communication	14.4	35.7	26.0	18.9	5.0
Social services	11.3	17.6	21.7	28.2	21.2
Other services	32.8	36.6	20.2	8.1	2.3
Total	18.5	27.7	24.1	18.9	10.7
1997					
Primary sector	28.1	27.4	17.7	10.9	15.9
Manufacturing industry	11.0	29.5	32.7	18.2	8.7
Nonmanufacturing industry	28.6	31.7	18.4	10.0	11.4
Commerce	12.4	23.4	30.6	24.1	9.5
Finance services or rent	2.7	5.4	16.1	40.3	35.6
Transportation or communication	9.1	26.8	32.2	23.9	8.0
Social services	6.0	13.2	21.1	29.6	30.0
Other services	26.2	35.7	24.6	11.1	2.4
Total	12.7	23.7	26.3	22.1	15.1

Source: Author's calculations based on the ENEU (third quarter).

Another relevant observation is that educational attainment by age group also improved, as the distribution by educational level was higher in 1997 than it was in 1988 (table 13). In an attempt to reach a better understanding of this event, it is interesting to contrast the time and cohort effects.[20] In order to do this, one can look at the first age groups, 16–25 and 26–34, like synthetic cohorts. Namely, the 26–34 age group in 1997 can be compared directly to the 16–25 age group in 1988, and, to a lesser extent, the 35–49 age group in 1997 can be compared to the 26–34 age group in 1988. From 1988 to 1997, the percentage of persons in the category of

20. The time effect refers to the comparison of the same age group in two different points of time.

incomplete primary schooling decreased, and this decline was higher than that experienced by the 16–25 age group (who were in the 26–34 age group in 1997). The opposite took place for the highest level of instruction. In other words, improvements throughout the educational process in Mexico were significant, both for those entering the system (higher coverage) and for those already in it (higher efficiency).

Table 13. Educational Distribution by Age Group, 1988 and 1997

(percent)

Age group	*Primary incomplete*	*Primary complete*	*Lower secondary complete*	*Upper secondary complete*	*University complete*
1988					
16–25	8.5	26.5	36.7	23.7	4.6
26–34	12.6	23.7	23.1	22.5	18.2
35–49	24.0	33.3	16.8	14.3	11.6
50–65	46.1	27.2	9.9	9.0	7.8
Total	18.5	27.7	24.1	18.9	10.7
1997					
16–25	5.8	23.8	38.7	25.5	6.2
26–34	6.9	19.5	28.1	27.0	18.5
35–49	14.8	25.8	19.5	19.1	20.7
50–65	37.3	27.6	11.5	10.6	13.0
Total	12.7	23.7	26.3	22.1	15.1

Source: Author's calculations based on the ENEU (third quarter).

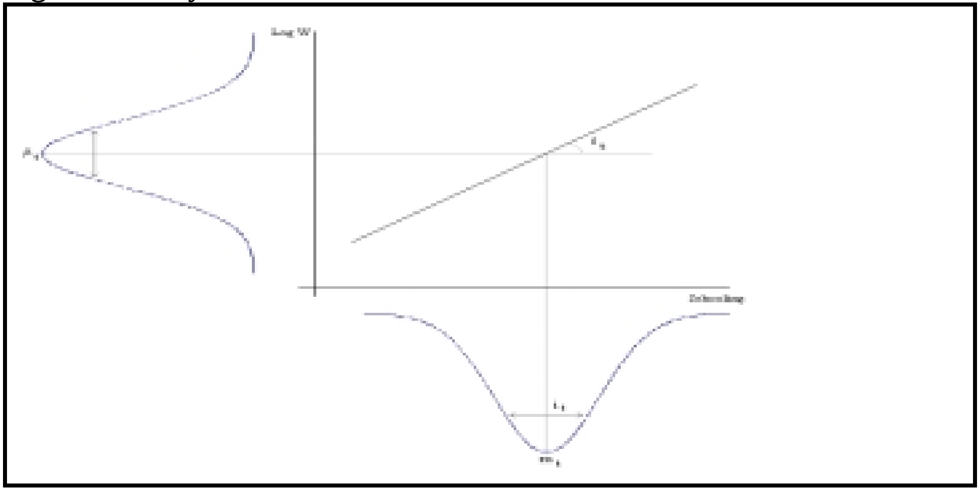
Also concerning the interaction between age and education, one can argue that developments in the educational system have more impact on the new generations than on the elderly. To investigate this, it is necessary to contrast the behavior of inequality between different age groups to that of inequality within synthetic cohorts and in relation to education. As seen, the younger cohorts are, in fact, better educated than the older ones. At the same time, the "within" income dispersion for the youngest cohorts seems to increase over time, compared with the internal Theil in 1997 and 1988 (see table 6). Thus it becomes easier to understand why the gross contribution of age to inequality has been rising, while its marginal contribution has been decreasing. In other words, differences in both educational attainment and distribution among cohorts have become pronounced in recent times, leading to a higher (negative) correlation between education and age.

V. The Dynamic Decomposition

In order to address the relationship between education (the result of the interaction between supply and demand) and earnings inequality, it is necessary to explain how the labor market determines the earnings differentials among workers with different educational attributes. This relationship can be viewed as determined by two elements: (a) the distribution of education itself and (b) the way the labor market rewards educational attainment. The first element reflects a preexisting social stratification that already entails some inequality due to reasons other than the workings of the labor market itself. The second is associated with the degree to which this preexisting inequality grows into earnings inequality due to the performance of the labor market (that is, demand behavior).

Figure 4 shows the distribution of education in the horizontal axis (m_t is an indicator of the average schooling of the labor force, and i_t represents its dispersion), while the vertical axis presents the distribution of earnings. The first quadrant depicts the interaction between the preexisting conditions (the distribution of education) and the workings of the labor market, through the steepness s_t of the income profile related to education. Therefore, at a point in time, (a) the higher m_t is, the larger are the average earnings; (b) the lower i_t is, the smaller is the earnings inequality; and (c) the higher s_t is, the higher is the growth of preexisting disparities, and, accordingly, the higher is the earnings inequality. As these indicators change over time, they will induce changes in the income distribution: changes in i_t, assuming s_t constant, will change earnings inequality due to changes in the composition of the labor force (the so-called allocation-population effect), whereas changes in s_t will alter the earnings differentials (the income effect).

Figure 4. A Stylized View of Education and Labor Market Interaction



Barros and Reis (1991) develop three synthetic measures for the indicators m_t (average schooling), i_t (schooling inequality), and s_t (income profile), based directly on the definition of the Theil T index (see annex 2). The figures for Mexico from 1988 to 1997 are presented in table 14. Average schooling improved somewhat, but the inequality of the distribution of education deteriorated, whereas the income profile, which is related to the returns to schooling, became much steeper. This means that there was a shift in demand toward highly skilled labor that was not met by an increase in supply. This probably occurred as a result of the accelerated pace of skill-biased technological change facilitated by the increased openness of the Mexican economy. The same pattern observed for the overall sample holds for the 16–25 age group: the m_t rose from 0.561 in 1988 to 0.574 in 1997; the i_t increased from 0.0196 to 0.0218, whereas the s_t doubled, rising from 0.0196 to 0.0383.

Table 14. Synthetic Indicators of Schooling Distribution and Income Profile, 1988–97

Year	*1988*	*1992*	*1996*	*1997*
m_t	0.476	0.491	0.511	0.510
i_t	0.066	0.069	0.076	0.075
S_t	0.066	0.102	0.122	0.111

Source: Author's calculations based on the ENEU survey (third quarter).

Methodology

The dynamic decomposition analysis is a suitable tool for translating this stylized view in quantitative results, giving one a better understanding of the socioeconomic transformations responsible for changes in the earnings distribution. Besides permitting identification of the relevant individual variables, it also helps in understanding the nature of the contribution of each variable to the evolution of earnings inequality over time.

Ramos (1990), following Shorrocks (1980), shows that it is possible to break down the change in inequality between two points in time. This is done according to whether the change can be attributed to changes in the socioeconomic groups relative to incomes, to group sizes, or to internal inequalities, through use of the Theil T index. In generic terms, as shown before in a slightly different way, for a given partition of the population, the inequality indexes of this class can be written as:

(2) $I = I(\alpha_g, \beta_g, I_g)$

where α_g is the ratio between the average income of group g and the average income of the whole population, β_g is the proportion of the population in group g, and I_g is the internal dispersion of incomes in group g.

Of course, the αs are related to the indicator s_t in the previous picture, and the βs refer to m_t and i_t. In this context, the *population* or *allocation effect* corresponds to the variation induced in the inequality index I by modifications in the allocation of the population among the groups (changes in the βs), with no direct changes in the group's relative incomes (αs).[21] The *income effect* corresponds to the changes in I induced by changes in group incomes (αs), without changing the groups' shares of the population (βs), and the internal effect is the change in the inequality caused only by modifications in dispersions at the group level (the I_gs).[22] The expressions corresponding to the Theil T index are derived in annex 2.

Results

The results of the decomposition of the variations in the Theil T index for different intervals of time are shown in table 15. First, when the variables are considered alone, education made the highest gross contribution to the changes in earnings distribution. Second, both the allocation and the income effect were positive in all periods. This means that changes in the distribution of education and in the relative earnings among educational groups were always in phase with alterations in the earnings distribution. Namely, when the income profile related to education became steeper and the inequality of education grew, the earnings distribution worsened (as in the 1988–92, 1992–96, and 1988–97 periods) and vice versa (as in the 1996–97 period).

21. The difference between this and what Knight and Sabot (1983) call the "compression" effect is that in the present exercise we are including the indirect change induced in I through the variation in the weights of the Igs. Of course, the individual's αs change as the βs change, since the overall average income is altered. This indirect impact is also computed in the composition effect (see annex 2).

22. The methodology applied by Fields (1996) and Bouillon, Legovini, and Lustig (1998) makes important assumptions. In contrast, Székely (1995), in order to explain the changes in inequality between two points in time, applies a methodology that differs drastically from the dynamic decomposition since he does not control for the effects that arise from changes in the population distribution and from changes in the relative earnings of income groups considered in the partition of the population (see annex 2).

Table 15. Results of the Dynamic Decomposition, 1988–97

Time period and variable	*Allocation*	*Income*	*Gross*	*Marginal*
1988–92				
Education	11.4	58.8	70.2	30.5
Age	-1.8	21.9	20.2	-5.2
Economic sector	-0.6	7.8	7.1	-17.7
Status	3.9	15.1	19.0	-7.4
1992–96				
Education	23.9	32.8	56.7	27.6
Age	11.1	10.5	21.6	10.5
Economic sector	-5.4	25.4	20.0	10.5
Status	1.2	12.4	13.6	-4.2
1996–97				
Education	2.2	15.5	17.7	24.2
Age	-0.4	5.9	5.5	12.5
Economic sector	0.4	1.0	1.4	18.4
Status	1.4	6.1	7.5	7.8
1988–97				
Education	35.8	108.4	144.1	33.7
Age	7.4	32.7	40.1	-19.9
Economic sector	-6.6	43.2	36.6	-40.6
Status	9.0	20.2	29.2	-35.6

Source: Author's calculations based on the ENEU (third quarter).

Third, the income effect is always prevalent. If one considers, for instance, the 1988–97 period, changes in the relative earnings among educational groups alone would have generated a larger deterioration in the earnings distribution than the one observed. To a lesser extent, the same holds true for the other periods.[23] Even the decrease in inequality observed between 1996 and 1997 is partially explained by the changes in relative earnings (the income profile related to education became less steep in this period, as shown in table 15). Therefore, it seems reasonable to conclude that the income effect is the leading force behind the increase in inequality, and this , in turn, suggests that the workings of the labor market, and its interaction with educational policies, should be thoroughly examined.

23. Of course, the explanation for such a phenomenon is that changes in the other variables attenuated the changes in the rewards to education.

Fourth, the significance of changes in the distribution of education remains high even when one controls for changes in other relevant variables.[24] As a matter of fact, with the exception of the 1996–97 transitional period, the marginal contribution of age, economic sector, and status in the labor market is usually negative. This means that changes in these variables reduced the effects induced by changes related to education, as most of the time they reduced inequality after the influence of education is taken into account.

The last period, from 1996 to 1997, deserves special comment. First, inequality was substantially reduced. Second, once more, alterations were associated with education, now working in the other direction, and such alterations appear to be the main factor responsible for the reduction in inequality. As can be seen from the synthetic indicators, there were a small improvement in the distribution of schooling during the period and a sizable decrease in the steepness of the income profile related to education. All other variables, as observed for other periods, also contributed to an improvement in earnings inequality.

Table 16 shows the results of the same kind of decomposition for Brazil, Argentina, and Peru. The significance of education as an explanation of changes in inequality seems to be a common pattern in Latin American countries. Moreover, the relevance of the income effect over the allocation (population) effect is also shared by all countries where a similar analysis was carried out. In the Mexican case, however, the figures are higher than those for other countries (and in a shorter period of time). This means that changes in the structure of supply and demand for labor, which are greatly affected by the educational and macroeconomic policies followed by

24. Székely (1995) concludes that, for the 1984–89 period, the variables that contributed significantly to explaining inequality were education and economic sector, while education and job status were significant in the 1984–92 period. The selected variables were education, occupation, region, economic sector, and job status. Bouillon, Legovini, and Lustig (1998), applying Bourguignon's methodology to the ENIGH, find that the return effect to the household characteristics (age/gender, education/age, assets) explained 49 percent of the increase in the Gini between 1984 and 1994, education being the most important explanatory variable. The region effect (urban/rural) was 9 percent, the south effect was 15 percent, and the population effect was 23 percent.

the country or by their interaction with the workings of the labor market, were particularly relevant for the earnings distribution.

Table 16. Education and Inequality Variation in Brazil, Argentina, and Peru

Country	*Study*	*Time period*	*Explanatory power (percent)*[a]	*Income effect (percent)*
Brazil	Ramos and Trindade (1991)	1977–89	6–20	10–17
Argentina	Fiszbein (1991)	1974–88	54–56	38–46
Peru	Rodríguez (1991)	1970–84	32–47	34–43

a. The income effect plus the allocation-population effect.

VI. The Evolution and Structure of the Rates of Returns to Education: An Application of Quantile Regression

The increase in earnings inequality is not the result of a worsening in the distribution of education, whereas the income profile, which is related to the returns to schooling, is much steeper. In light of this evidence, this section analyzes the structure and evolution of the rate of returns to education. Although this is a common procedure, this is an important caveat, as the international comparison becomes cumbersome because the structure of the educational process in Mexico is different than that of other countries.

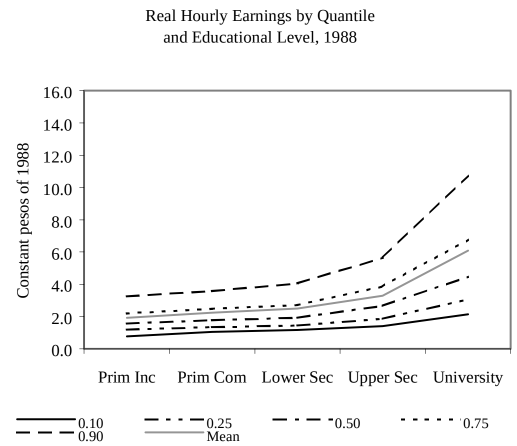
Quantile Analysis

Before estimating the rate of returns to education, it is necessary to take a preliminary look at the relationship between the distribution of earnings and educational attainment in Mexico. For this purpose, real hourly earnings by quantile (0.10, 0.25, 0.50, 0.75, and 0.90) and the mean are computed.[25]

25. The third quarter of the ENEU data for 1988, 1992, and 1996 is used. The sample is described in the appendix.

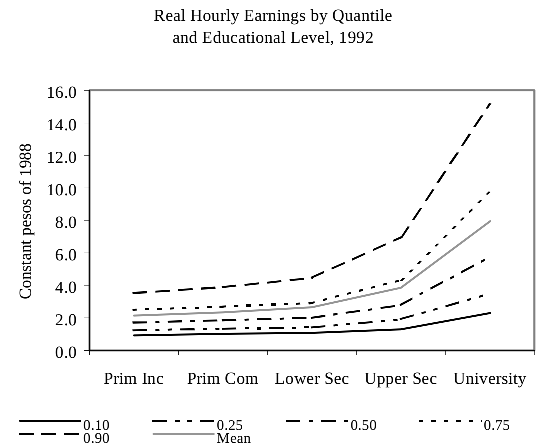
As can be seen from figures 5 through 7, the curves do not cross each other for all educational categories or for all periods. This suggests that there is a strict dominance of the education variable throughout the earnings distribution. In other words, there is a positive relation between educational level and hourly earnings throughout the distribution. Those figures also show that the difference among quantiles (that is, from the tenth to the twenty-fifth percentile, from the twenty-fifth to fiftieth percentile, and so forth) changes throughout educational levels (the greater is the level of education, the larger is the difference among quantiles of hourly earnings). In addition, the difference between quantiles also changes through time. These patterns may provide empirical evidence that there are differences in the increase in real hourly earnings throughout educational distribution and time. The quantile analysis provides a complete assessment of the impact of many variables (education, age, gender, economic sector, labor market status, region, and so forth) throughout the earnings distribution. Finally, for all educational categories, real average hourly earnings are greater than the median, and the distribution of hourly earnings is always right-skewed.

Figure 5.



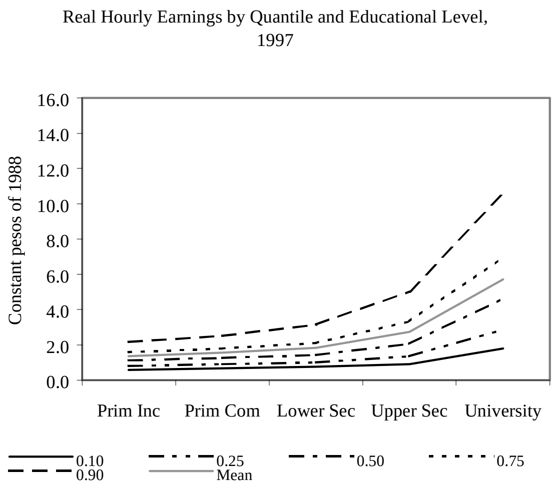
Source: Author’s calculations based on ENEU.

Figure 6.



Source: Author’s calculations based on ENEU.

Figure 7.



Source: Author’s calculations based on ENEU.

In sum, these results suggest that a quantile method of estimation is needed to provide a better understanding of the rate of returns to education.

Methodology

One way to estimate the returns to schooling is by using conventional Mincerian earnings equations based on the human capital paradigm, with controls for other characteristics (individual attributes or labor market traits) that might influence the differentials. This approach allows one to disentangle the association between individual earnings and levels of education from the joint influence of other variables on earnings.

In this study, an ad hoc, yet usual, specification is used, with control variables for age (used as a rough proxy for experience), labor market status, economic sector allocation, and geographic region.[26] Then the earnings function can be described as follows:

(3) $\log\ Y_t = a_t + S_t b_t + X_t c_t + u_t, \quad t = 1988,\ 1992,\ 1996,\ \textit{and}\ 1997$

where

Y_t Vector of individual hourly earnings in time *t*

a_t Logarithm of the mean real hourly earnings of the reference group in time *t*

b_t Earnings differential associated with education in time *t*[27]

c_t Vector of earnings differentials related to the control variables in time *t*

S_t Vector of educational attainment in time *t*

X_t Matrix of control variables for time *t*

u_t Vector of residual terms for time *t* [$E(u_t) = 0$ and $E(u_t u_t^`) = 0$].[28]

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26. All of these variables are categorical, with the exception of age. Therefore, it is necessary to leave one category (reference group) per variable out of the regression in order to avoid perfect collinearity. Primary incomplete (education), formal salaried workers (labor market status), manufacturing (economic sector), and Mexico City (region) were left out.
27. As this is a categorical variable, one has, in fact, a vector (b_{it}) of earnings differentials, with each of its components representing the earnings differential between the *i*th educational group and the reference group (primary incomplete) in time *t*.
28. In addition, one has to assume that the residual term is not correlated with the unobserved determinants of individual earnings (family background, natural ability, and so forth).

These earnings functions can be fitted using least squares estimation. However, a new technique of estimation has been developed recently: quantile regression. This technique usually has been applied to analyze the determinants of wage structure as well as the rate of returns to investment in education throughout the earnings distribution. Buchinsky (1994, 1995, 1998) applies this technique to the U.S. labor market in order to assess the wage structure and its changes. Other authors also used quantile regression to study the pattern of U.S. wage differentials between state and local government employees and their private counterparts. The quantile regression analysis also has been applied to other countries: Shultz (1998) and Muller (1998) in Canada, Abadie (1997) in Spain, and Montenegro (1998) in Chile. This methodology has never been applied in Mexico. This papers follows closely the methodology proposed by Buchinsky (1994, 1995, 1998). [29]

The quantile regression models have some desirable characteristics, especially for analyzing a certain variable throughout its distribution. The main features of these models can be summarized as follows:

- The model can be used to characterize the entire conditional distribution of the dependent variable.
- The quantile regression objective function is a weighted sum of absolute deviations, which gives a robust measure of location, so that the estimated coefficient vector is not sensitive to outlier observations of the dependent variable.
- When the error term is non-normal, quantile regression estimators may be more efficient than least squares estimators.

[29] The author shows that the quantile method is robust even in the presence of possible self-selection.

- Different solutions at distinct quantiles may be interpreted as differences in the responses of the dependent variable to changes in the independent variables at various points in the conditional distribution of the dependent variable (see Buchinsky 1998).
- The earnings function (equation 3) can be rewritten as a quantile regression model. Then we have $\log Y_i = X_i\beta_\theta + \mu_\theta$ with $\text{Quant}_\theta(\log Y_i|X_i) = X_i\beta_\theta$ ($I = 1, \ldots, n$), where β_θ and X_i are Kx1 vectors, and $X_{i1} \equiv 1$. $\text{Quant}_\theta(\log Y|X)$ denotes the θth conditional quantile of Y given X. Also let $f_{\mu_\theta}(\cdot|X)$ denote the density of μ_θ given X. It follows that $\text{Quant}(\mu_\theta.|X) = 0$.

The X_i vector includes the set of explanatory dummy variables as well as the controls. For an extensive review, see Buchinsky (1998).

By using the regression coefficients, one can compute the differentials and marginal value related to each level of education. According to the specification of the earnings functions, for least squares as well as for quantile regression, the exponential of the differential associated with the jth category of the ith variable, $\exp(c_{ij})$, corresponds to an estimate of how much higher, on average, the earnings of an individual in that category are relative to the earnings of an individual in the reference group for that variable, all other attributes being identical.[30] The marginal value of some educational level j in time t (MV_j^{educ}) can be interpreted as the earnings differential for this level relative to the previous one, as follows:[31]

(4) $$MV_{jt}^{educ} = b_{jt} / b_{(j-1)t} \quad \text{for } j > 1 \text{ and}$$

$$MV_j^{educ} = b_{jt} \quad \text{for } j = 1$$

30. If the differential is close to zero, then it can be interpreted as being approximately equal to the average percentage increase in earnings associated with a movement from the reference group to jth category, ceteris paribus.
31. Similarly, the definition applies to the results of the quantile regression approach. The only difference is that in

Empirical Results

Both ordinary least squares and quantile regression models are estimated.[32] However, before analyzing the rate of returns to education, it is worth investigating the role of each explanatory variable in the determination of earnings. For this purpose, several regressions are fitted adding the explanatory variables one at a time. This exercise has two advantages: (a) it allows us to assess the marginal contribution of each explanatory variable, and (b) it shows the explanatory power of each variable throughout the conditional earnings distribution. Cragg and Epelbaum (1996) perform a similar exercise as well as other authors such as Meza (1999) and Rojas (2000). Nevertheless, the occupation variable was left out of this study, since as structured in ENEU-INEGI questionnaires, it is highly correlated to the individual's level of education. As shown in table A3.2, educational level and occupation are highly correlated, while education and the rest of the explanatory variables are weakly correlated.

Education is the most important variable in the explanation of earnings inequality. However, we can assess the importance of other explanatory variables using the estimates of differentials in educational level. If the changes in such differentials, in a given period of time, have been smoothed by some other explanatory variable, then that variable is a measure of some specific skill. For doing such an assessment, we compute the relative change in the differentials by educational level in 1988–92 and 1992–97 periods. The estimates are presented below.

Table 17 shows that earnings differentials were reduced by introduction of the economic sector variable in the regression for the 1992–97 period, particularly for tertiary education, while the reduction was very small for the 1988–92 period (see Cragg and Epelbaum 1996). Labor

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this situation one needs an additional subscript (θ) to assign the quartile.

32. The θs parameters in the quantile regression were 0.1, 0.25, 0.5, 0.75, and 0.9, following a common procedure in

market status seems to have the same reduction effect on earnings differentials as the economic sector variable. These results suggest that the degree of correlation between education and economic sector, as well as labor market status, increased through time. Table 17 also shows that region had an almost insignificant effect on earnings differentials.

Table 17. Change in Differentials Controlling for Economic Sector, Labor Market, Status, and Region, 1988–97

	Controlling for none		*Economic sector*		*Status*		*Economic sector and status*		*Economic sector, region, and status*	
Education level	*1988–92*	*1992–97*	*1988–92*	*1992–97*	*1988–92*	*1992–97*	*1988–92*	*1992–97*	*1988–92*	*1992–97*
Primary complete	-0.03	0.05	-0.01	0.02	-0.04	0.03	-0.02	0.02	-0.02	0.01
Lower secondary complete	-0.06	0.08	-0.05	0.03	-0.06	0.03	-0.03	0.00	-0.03	0.00
Upper secondary complete	-0.02	0.11	0.02	0.04	-0.02	0.04	0.01	0.00	0.01	0.00
University complete	0.14	0.18	0.15	0.08	0.12	0.09	0.15	0.04	0.15	0.04

Note: Least squares estimates. The reference group is primary incomplete.

Source: Author's calculations based on ENEU (third quarter).

At this point, one tentative conclusion emerges: the reduction effect on earnings differentials of both economic sector and labor market status variables was significantly larger in 1992–97 than in 1988–92 (before the trade agreement). This means that the relationship between education and the types of specific skills acquired through such variables changed in the labor market. Thus a worker's insertion into the labor market and economic sector variables were a consequence of skills differentials and attributed not solely to education. In order to have a precise assessment of the marginal value to educational level, the analysis must incorporate this based on the earnings regression conditioned on economic sector, labor market status, region, as well as age, age squared, and gender.

the literature.

Table 18 presents the marginal value of education by level. In the regression estimates, all the coefficients for education were significant at the 5 percent level, and the results for the marginal value of each educational level are reported in the table.

Table 18. Marginal Value of Education by Level of Education and Quantile, 1988–97

Year and level of education	*0.10*	*0.25*	*0.50*	*0.75*	*0.90*	*OLS*
1988						
Primary complete	1.15	1.15	1.16	1.18	1.19	1.19
Lower secondary complete	1.11	1.11	1.14	1.17	1.20	1.17
Upper secondary complete	1.13	1.18	1.23	1.26	1.26	1.27
University complete	1.34	1.39	1.44	1.46	1.52	1.49
1992						
Primary complete	1.12	1.13	1.13	1.14	1.16	1.16
Lower secondary complete	1.10	1.12	1.15	1.18	1.21	1.15
Upper secondary complete	1.20	1.25	1.30	1.35	1.39	1.32
University complete	1.46	1.54	1.66	1.70	1.69	1.69
1996						
Primary complete	1.14	1.14	1.15	1.17	1.20	1.15
Lower secondary complete	1.12	1.13	1.15	1.18	1.20	1.16
Upper secondary complete	1.21	1.25	1.31	1.40	1.48	1.34
University complete	1.60	1.71	1.80	1.78	1.70	1.74
1997						
Primary complete	1.15	1.16	1.17	1.18	1.18	1.18
Lower secondary complete	1.11	1.12	1.14	1.18	1.22	1.14
Upper secondary complete	1.20	1.25	1.31	1.39	1.47	1.32
University complete	1.63	1.76	1.80	1.77	1.70	1.75

Note: The marginal value is with respect to the previous educational level. The asymptotic covariance matrix of the estimated coefficient vector in quantile regression is computed using the bootstrap method. All the coefficients are statistically significant at 5 percent and are conditioned to age, age squared, gender, status in the labor market, economic sector, and region (north, center, south, and Mexico City).

Source: Author's calculations based on ENEU (third quarter).

In general, the ordinary least squares (OLS) estimates are quite similar to the ones obtained by the quantile regression approach for $\theta = 0.5, 0.75$. It is true, nevertheless, that the estimates through the quantile regression technique tend to increase as one moves from the right to the left of the conditional earnings distribution, particularly for the upper levels of education. In summary, the results have three strong implications: (a) education does play a crucial role in the process of earnings formation, (b) its effect is not the same throughout the conditional earnings distribution, and (c) the marginal value of education has not changed significantly in basic education.

Specifically, one can say that the rewards to education display a log-convexity for all years investigated. This log-convexity, however, became pronounced in the 1988–96 period, as the marginal value for the higher levels increased relatively more. This trend reversed in 1997, basically due to the gains associated with complete primary education and losses associated with upper secondary, though in a slight way.

The accumulated changes in the marginal value of education by level are not significant for the levels of complete primary and lower secondary instruction, along with the conditional earnings distribution for OLS estimates (see table 19). This does not apply for upper secondary education, as the changes were substantial and very progressive across quantiles (8 percent at the median and 23 percent at the top decile). The changes were more important for the university level.

Table 19. Percentage Change in the Marginal Value of Education, by Quantile, 1988–97

Level of education	*0.1*	*0.25*	*0.5*	*0.75*	*0.9*	*OLS*
Primary complete	0	1	1	0	-1	-1
Lower secondary complete	1	1	0	1	2	-3
Upper secondary complete	7	7	8	14	23	5
University complete	34	45	43	36	20	30

Source: Autho'rs calculations based on ENEU.

In sum, the returns to education have increased in Mexico in recent times, especially for higher levels of education and in the upper tail of the conditional earnings distribution.

Rate of Returns to Education and Inequality

The “between” probability is the mobility of unskilled and skilled workers between *j* and *k* economic sectors.[33] By contrast, the “within” mobility depicts workers who move across subsectors or occupations. Table 20 presents the transition probabilities for the respective periods. On the one hand, the financial services sector shows a clear trend to substitute unskilled labor for skilled labor: the probability of workers changing to another economic sector is much higher for unskilled workers (70 percent) than for skilled workers (21 percent). The primary sector follows the same trend only at the end of the 1980s. On the other hand, nonmanufacturing industry is substituting skilled for unskilled workers. Finally, manufacturing industry and transportation and communications do not have a clearly dominant probability of hiring either skilled or unskilled workers.

33. The transition probabilities describe the shifts of skilled and unskilled workers within and across sectors. The transition probabilities are the conditional probability of finding a worker in economic sector *k* at the end of the period given that the worker began in sector *j*. This probability gives us the mobility of less- and high-skilled workers between *j* and *k* economic sector. Skilled workers are those individuals with more than 12 years of schooling.

Table 20. Transition Probabilities of Being in the Same Sector, Change within Sector, and Change between Sector, by Level of Education, 1988–97

Level of education and sector	*1988–89* *No change*	*Sector change* *Within*	*Between*	*1992–93* *No change*	*Sector change* *Within*	*Between*	*1996–97* *No change*	*Sector change* *Within*	*Between*
Upper secondary incomplete or lower									
Primary sector	46.4	14.4	39.3	28.5	46.8	24.7	47.8	13.6	38.6
Manufacturing industry	52.7	24.5	22.7	53.6	23.1	23.4	56.9	24.5	18.6
Nonmanufacturing industry	45.6	11.8	42.6	50.3	7.6	42.1	46.9	9.4	43.7
Commerce	48.0	16.2	35.7	60.3	14.0	25.6	53.6	17.7	28.7
Financial services or rent	25.7	4.1	70.2	35.6	8.0	56.4	67.6	2.7	29.6
Transportation or communication	65.1	6.7	28.2	71.7	8.0	20.2	72.5	8.4	19.0
Social services	59.0	21.2	19.8	61.6	18.3	20.2	66.9	14.7	18.4
Other services	59.7	8.8	31.5	65.7	4.9	29.4	60.5	2.3	37.2
Weighted average	54.2	17.5	28.3	58.7	15.3	26.0	59.2	14.6	26.1
Upper secondary complete or higher									
Primary sector	41.3	0.0	58.7	42.3	6.1	51.6	35.4	21.2	43.4
Manufacturing industry	42.3	29.9	27.8	50.7	24.7	24.6	53.2	27.4	19.3
Nonmanufacturing industry	57.7	8.1	34.1	51.0	15.4	33.6	54.0	6.5	39.4
Commerce	41.9	13.6	44.4	52.2	15.4	32.4	51.6	15.4	33.0
Financial services or rent	77.0	1.3	21.6	69.2	6.1	24.7	66.2	18.6	15.1
Transportation or communication	50.9	18.9	30.2	74.7	8.3	17.0	69.6	6.1	24.4
Social services	55.1	34.0	10.9	63.8	23.2	13.0	71.5	18.2	10.3
Other services	45.1	4.4	50.4	56.5	0.5	43.0	56.5	1.4	42.0
Weighted average	51.1	25.1	23.8	59.1	19.1	21.8	64.0	17.4	18.7

Note: The length of time is one year. The sample includes those in the labor force and in the panel. Sector change within sector is defined according to change between subsectors.
Source: Authors' calculations based on the ENEU survey (third quarter).

Using shifts both "within" and "between" economic sectors, one can explore the effect of these shifts on the relative wage of skilled and unskilled workers. Table 20 also shows that, for all periods considered, the "between" probability of having a skilled versus an unskilled labor force is substantially higher; conversely, the "within" probability of having a skilled labor force is significantly lower than that of having an unskilled one. Therefore, one might infer that the relative wage of unskilled labor relative to skilled labor increased, derived from shifts within economic sectors. However, this effect might have been partially offset by the decrease in relative wages of unskilled labor relative to skilled labor, derived from the shift between economic sectors. Given the rate of returns to education, it is plausible to infer that the shifts in relative demand within economic sectors dominated the shifts in relative demand between sectors.

With the goal of putting the rate of returns in perspective, table 21 shows the percentage of earnings differentials for other Latin American countries. Mexico is above the average, second only to Brazil (the country with the highest inequality in Latin America). Once more, this indicates that educational policies must be at the core of any effort aimed at reducing inequality and, by extension, poverty in Mexico.

Table 21. Earnings Differentials in Latin America, by Country

(percent)

Level of education	*Latin America*	*Mexico*	*Brazil*	*Argentina*	*Peru*
Primary complete	50	100	100	35	40
Upper secondary complete	120	170	170	80	80
University complete	200	260	280	160	145

Note: Reference group is no schooling.

Source: IDB (1998 -1999).

VII. Conclusions

Even though the levels of educational attainment expanded very rapidly, Mexico has experienced a pronounced increase in the degree of income inequality over the period of analysis. Most of the deterioration in the distribution of total current income happened in the middle to late 1980s (1984–89). The early 1990s displayed little change in total current income inequality except for a slight trend toward deterioration. The trends in the distribution of earnings differ from the trends in the distribution of current income in two ways. First, the gains are not limited to the richest 10 percent, as those in the seven-, eight-, and nine-tenths of the distribution improved their relative earnings over the period by almost 2 percentage points. Second, the distribution of earnings clearly worsened in the 1990s until 1996, although the inequality associated with total current income was moderately stable in the 1990s, displaying an improvement in 1996. Differences in the behavior of total current income and labor earnings inequalities from 1994 to 1996 support the idea that the poor, who rely the most on labor as a source of income, are the least able to protect themselves during a recession.

Educational inequality is the variable that accounts for by far the largest share of earnings inequality in Mexico, both in terms of gross and marginal contribution. The contribution of education to earnings inequality in Mexico is the second highest in Latin America. Moreover, what seems to be particularly interesting in the Mexican experience is the fact that the significance of education has been increasing over time.

The increase in earnings inequality, however, does not appear to be the result of a worsening in the distribution of education, whereas the income profile, which is related to the returns to schooling, has become much steeper. This means that there was a shift in demand toward high-skilled labor that was not met by an increase in supply. This probably occurred as a result of the rapid rate of skill-biased technological change, whose transmission to Mexico was facilitated by the economy’s increased openness.

Annex 1. Data Sources

The National Household Income and Expenditure Survey (ENIGH) and the National Urban Employment Survey (ENEU) were used in this study.

ENIGH

The National Household Income and Expenditures Survey is collected by the Instituto Nacional de Estadística, Geografía e Informática (INEGI). This survey is available for 1984, 1989, 1992, 1994,1996, 1998[34]. Each survey is representative at the national level, urban and rural areas. For 1996, the ENIGH is also representative for the states of Mexico, Campeche, Coahuila, Guanajuato, Hidalgo, Jalisco, Oaxaca and Tabasco.

For each year the survey design was stratified, multistage and clustered. The final sampling unit is the household and all the members within the household were interviewed. In each stage, the selection probability was proportional to the size of the sampling unit. Then, it is necessary to have the use of weighs[35] in order to get suitable estimators. The table below shows the sample size for each year.

Table 1.A1 Sample Size by Year

Year	Number of households	Number of persons
1984	4,735	23,756
1989	11,531	56,727
1992	10,530	50,378
1994	12,815	59,835
1996	14,042	64,359

The available information can be grouped into three categories:

- Income and consumption: the survey has monetary, no monetary and financial items.
- Individual characteristics: social and demographic, i.e., age, schooling attendance, level of schooling, position at work, sector, etc.
- Household characteristics.

Category Selection

For the purpose of the analysis, the individuals in the sample were classified according to their educational level, position in occupation, sector of activity and geographical region in the following categories:

Educational level

a) Primary incomplete: no education and primary incomplete (one to five years of primary)
b) Primary complete: primary complete and secondary incomplete (one or two years)
c) Secondary complete: secondary complete and preparatory incomplete (one or two years)
d) Preparatory complete: preparatory complete and university incomplete
e) University complete: university complete (with degree) and postgraduate studies

[34] The sample in a given year is independent from another.
[35] The weights should be calculated according to the survey design and corresponds to the inverse of the probability inclusion.

Position in occupation

a) Worker or employee
b) Employer
c) Self employed

Sector of activity

a) Agriculture
b) Manufacturing
c) Construction
d) Commerce
e) Services
f) Other (utilities, extraction, transports, financial services, communications, etc)

Geographical regions

a) North: Baja California, Baja California Sur, Coahuila, Chihuahua, Durango, Nuevo Leon, Sinaloa, Sonora, Tamaulipas and Zacatecas
b) Center: Aguascalientes, Colima, Guanajuato, Hidalgo, Jalisco, Mexico, Michoacan, Morelos, Nayarit, Puebla, Queretaro, San Luis Potosi and Tlaxcala
c) South: Campeche, Chiapas, Guerrero, Oaxaca, Quintana Roo, Tabasco, Veracruz and Yucatan
d) Distrito Federal.

Group Selection

The labor force was limited to individuals who are:

a) working as employee, employer or self employed[36];
b) between 12 and 65 years old;
c) living in urban areas;
d) working 20 hours or more per week;
e) with positive income;
f) having the attributes of interest defined.

The number of persons in the survey that belong to the labor force is shown in the next table.

Table 2. A1. Sample size for the labor force

Year	Number of persons	% of the total sample
1984	3,892	16.4
1989	10,401	18.3
1992	8,752	17.4
1994	10,982	18.4
1996	12,996	20.2

[36] The respective categories: workers without payment and cooperative members were excluded because of the sample size.

According to the groups mentioned we have that,

Table 3. A1 Sample size by variable and year

Variable	**1984**	**1989**	**1992**	**1994**	**1996**
Education Level					
Primary Incomplete	1,246	1,951	1,879	2,387	2,736
Primary Complete	1,299	3,006	2,501	2,975	3,411
Secondary Complete	803	2,875	2,489	3,014	3,734
Preparatory Complete	389	1,614	1,168	1,617	1,915
University Complete	245	955	715	989	1,200
Position in Occupation					
Employee	3,175	8,604	7,188	8,843	10,207
Employer	126	311	393	450	610
Self employed	681	1,486	1,171	1,689	2,179
Total	3,982	10,401	8,752	10,982	12,996

ENEU

This study uses information from the National Urban Employment Survey (ENEU), which is also a micro-level data set collected by (National Institute of Statistics and Geography of Mexico) INEGI and contains quarterly wage and employment data over the past 10 years (1987–97). According to INEGI's methodology document on the ENEU, the data are representative of the 41 largest urban areas in Mexico, covering 61 percent of the population in urban areas with at least 2,500 inhabitants and 92 percent of the population living in metropolitan areas with 100,000 or more inhabitants. In 1985 the ENEU included 16 urban areas: Mexico City, Guadalajara, Monterrey, Puebla, León, San Luis Potosí, Tampico, Torreón, Chihuahua, Orizaba, Veracruz, Mérida, Ciudad Juárez, Tijuana, Nuevo Laredo, and Matamoros, covering 60 percent of the urban population for that year. In 1992, 18 more urban areas were included in the survey: Aguascalientes, Acapulco, Campeche, Coatzacoalcos, Cuernavaca, Culiacán, Durango, Hermosillo, Morelia, Oaxaca, Saltillo, Tepic, Toluca, Tuxtla Gutiérrez, Villahermosa, Zacatecas, Colima, and Manzanillo. In 1993 and 1994 Monclova, Querétaro, Celaya, Irapuato, and Tlaxcala entered the ENEU. Finally, Cancún and La Paz joined the survey in 1996. According to INEGI, the ENEU always has covered about 60 percent of the national urban population.

The data are from household surveys, which fully describe family composition, human capital acquisition, and experience in the labor market (the variables contain information about social household characteristics, activity condition, position in occupation, unemployment, main occupation, hours worked, earnings, benefits, secondary occupation, and search for another job). As with the ENIGH, the sampling design was stratified in several stages (where the final selection unit was the household) and with proportional probability to size.37 This statistical construction allowed us to make comparisons among different years. Moreover, this survey is structured to generate a panel data set that conforms with a rotator or rotating panel (a fifth of the total sample goes out and a new one comes in every quarter). Hence, the panel data follow the same household throughout five quarters.

Category Selection

The individuals in the sample were classified according to their educational level, age, sector of activity, position in occupation, hours worked, and geographic region in the following categories:

Educational level

a) Primary incomplete: no education and primary incomplete (one to five years of primary)
b) Primary complete: primary complete and secondary incomplete (one or two years)
c) Secondary complete: secondary complete and preparatory incomplete (one or two years)
d) Preparatory complete: preparatory complete and university incomplete
e) University complete: university complete (with degree) and postgraduate studies

37. For this it was necessary to use weights or expansion factors.

Age

a) 12 to 25 years old
b) 26 to 34 years old
c) 35 to 49 years old
d) 50 to 65 years old

Sector of activity

a) Primary sector (includes agriculture, forestry, fishing, and mining).
b) Manufacturing industry
c) Nonmanufacturing industry (includes construction and utilities)
d) Commerce
e) Finance services and rent
f) Transportation and communication
g) Social services (tourism, education, health, public administration, embassy)
h) Other services

Labor market status

a) Employer
b) Self-employed
c) Informal salaried: people who work in an enterprise with 15 or fewer workers and do not receive social security (IMSS, ISSTE, private, and so forth)
d) Formal salaried: people who work in an enterprise with 16 or more workers or receive social security (IMSS, ISSTE, private, and so forth)
e) Contract

Hours worked

a) 20 to 39 hours a week
b) 40 to 48 hours a week
c) At least 49 hours a week

Geographic regions

a) North: Baja California, Baja California Sur, Coahuila, Chihuahua, Durango, Nuevo León, Sinaloa, Sonora, Tamaulipas, and Zacatecas
b) Center: Aguascalientes, Colima, Guanajuato, Hidalgo, Jalisco, Mexico, Michoacán, Morelos, Nayarit, Puebla, Querétaro, San Luis Potosí, and Tlaxcala
c) South: Campeche, Chiapas, Guerrero, Oaxaca, Quintana Roo, Tabasco, Veracruz, and Yucatán
d) Distrito Federal.

Group Selection

Analogous to the ENIGH, the sample consists of individuals who are:

a) Between 16 and 65 years old
b) Living in urban areas (localities with at least 2,500 inhabitants)
c) Working regularly (nonseasonal workers)
d) Working 20 hours or more a week
e) Having positive earnings38
f) Having the attributes of interest defined.

Table 4A.1. presents the sample size and labor force.

38. In this survey an additional adjustment had to be made: if the worker got a bonuus at the end of the year (*aguinaldo*), then the wage was expanded (we assumed that this benefit was equivalent to 30 days of wages a year).

Table 4A.1. Sample Size, 1988–97
(number of persons)

Year	Labor force	Total
1988	124,322	45,870
1989	125,820	47,630
1990	127,387	48,109
1991	126,262	48,080
1992	235,696	91,279
1993	239,394	90,860
1994	246,906	102,105
1995	252,563	100,838
1996	262,478	108,159
1997	272,356	116,559

Annex 2. Methodological Note

Gini Index

The Gini index is defined by

$$GI = \frac{2\,\mathrm{cov}[Y, F(Y)]}{\mu} \qquad (1)$$

where Y is the distribution of per capita income Y = (y1, …, yn), where yi is the per capita income of individual i, I = 1, …, n;μ is the mean per capita income; F(Y) is the cumulative distribution of total per capita income in the sample (that is, F(Y)=[f(y1),…f(yn)], where f(yi) is equal to the rank of yi divided by the number of observations [n]).39

Equation 1 can be rewritten and expanded into an expression for the Gini coefficient that captures the "contribution to inequality" of each of the K components of income (see Leibbrandt and others 1996).

$$GI = \sum_{k=1}^{K} R_k G_k S_k \qquad (2)$$

where Sk is the share of source k of income in total group income (that is, Sk = μk / μ), Gk is the Gini coefficient measuring the inequality in the distribution of income component k within the group, and Rk is the Gini coefficient of income from source k with total income.40

The larger is the product of these three components, the greater is the contribution of income from source k to total inequality.

Theil T Index41

This index is calculated as follows:42

$$T = \left(\frac{1}{n}\right)\sum_{i=1}^{n}\left(\frac{Y_i}{\overline{Y}}\right)\ln\left(\frac{Y_i}{\overline{Y}}\right) \qquad (3)$$

where Y_i is the income of the ith individual, $\overline{Y}$ is average income, and n is population size.

Static decomposition of the Theil index. If the population is divided into G groups with ng observations each, it is then possible to write equation 3 as:

$$T = \sum_{g=1}^{G}\left(\frac{1}{n}\right)\sum_{i=1}^{n_g}\left(\frac{Y_{ig}}{\overline{Y}}\right)\ln\left(\frac{Y_{ig}}{\overline{Y}}\right) \qquad (4)$$

where Y_{ig} is the income of the ith individual of the gth population subgroup.

If we now define $\beta_g = {n_g}/{n}$ and $Z_g = {\overline{Y}_g}/{k}$ where $\overline{Y}_g$ is the average income of the gth group and k is a reference income, it is possible to show, after some algebraic manipulation, that T can be expressed as:

$$T = \left(\frac{1}{k}\right)\sum_{g=1}^{G}\beta_g\, Z_g\, \ln Z_g - \ln k + \left(\frac{1}{k}\right)\sum_{g=1}^{G}\beta_g\, Z_g\, T_g \qquad (5)$$

where k = ΣβgZg and T_g is the Theil index for the gth group.

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39. Both the covariance and cumulative distribution are computed using the household weights.

40. *Rk* is defined as: $R_k = \dfrac{\mathrm{cov}[Y_k, F(Y)]}{\mathrm{cov}[Y_k, F(Y_k)]}$.

41. TheTheil T index is sensitive to changes at the bottom and the top tail of the distribution.

42. The mathematical notations in this section and the next follows Ramos (1990).

The first two terms on the right-hand side of equation 5 correspond to the between group inequality, and the third corresponds one to the within group inequality.

Choosing the mean income as the reference income—that is, $Z_g = \alpha_g = \bar{Y}_g / \bar{Y}$ —expression 5 simplifies to:

$$T = \sum_{g=1}^{G} \alpha_g \; \beta_g \; \ln \alpha_g + \sum_{g=1}^{G} \alpha_g \; \beta_g \; T_g \qquad (6)$$

The first term in equation 6 is the between group inequality, and the second term is the within group inequality.

Dynamic decomposition analysis. By totally differentiating equation 6, we have:

$$dT = \sum_{g=1}^{G} \frac{\partial T}{\partial \beta_g} d\,\beta_g + \sum_{g=1}^{G} \frac{\partial T}{\partial \alpha_g} d\,\alpha_g + \sum_{g=1}^{G} \frac{\partial T}{\partial T_g} d\,T_g \qquad (7)$$

The first term on the right-hand side is the population allocation effect (changes in T caused exclusively by population shifts). The second term is the income effect (changes in T induced exclusively by changes in standardized mean incomes), and the third one is the internal effect (changes in T caused by changes in internal dispersion).
It can be shown that:

$$\frac{\partial T}{\partial \beta_g} = \alpha_g \ln \alpha_g - \alpha_g \sum_{g=1}^{G} \alpha_g \; \beta_g \; (1 + \ln \alpha_g) + \alpha_g \; T_g - \alpha_g \sum_{g=1}^{G} \alpha_g \; \beta_g \; T_g \qquad (8)$$

$$\frac{\partial T}{\partial \alpha_g} = \beta_g (1 + \ln \alpha_g) - \beta_g \sum_{g=1}^{G} \alpha_g \; \beta_g \; (1 + \ln \alpha_g) + \beta_g \; T_g - \beta_g \sum_{g=1}^{G} \alpha_g \; \beta_g \; T_g \qquad (9)$$

$$\frac{\partial T}{\partial T_g} = \alpha_g \, \beta_g \qquad (10)$$

Replacing equations 8, 9, and 10 into equation 7 and simplifying, we obtain

$$dT = \sum_{g=1}^{G} \alpha_g (\ln \alpha_g + T_g - T - 1) \; d\,\beta_g + \sum_{g=1}^{G} \beta_g (\ln \alpha_g + T_g - T) \; d\,\alpha_g + \sum_{g=1}^{G} (\alpha_g \, \beta_g) \; d\,T_g \qquad (11)$$

The three terms on the right-hand side of equation 11 correspond to the allocation, income, and internal effects, respectively.
For estimation purposes, equation 11 must be approximated. The convention used in the empirical exercises is to evaluate the expression at the middle points.

Level, Inequality, and the Indicator of Steepness of the Income Profiles in Educational Level

Ramos (1990) uses three synthetic measures for the indicators m_t (average schooling), i_t (schooling inequality), and s_t (income profile), based directly on the definition of the Theil index.
The calculations of the principal parameters αg, βg, and Tg (5) could determine the changes in the distribution by level of education (g groups in this category). These parameters allow us to analyze the trend in educational income differentials, the distribution of the population in each educational level, and the inequality among them.

Three synthetic measures are used to summarize the changes related to education: m_t is the average level of schooling for the year t, i_t is the degree of inequality in the distribution of education for year t, s_t is the variation in the income ratios associated with education for year t.
These measures can be calculated as follows:

$$m_t = \sum_g \alpha_g^* \beta_g^t$$

$$i_t = \frac{\sum_g \alpha_g^* \beta_g^t \log(\alpha_g^*)}{\sum_g \alpha_g^* \beta_g^t} - \log\left(\sum_g \alpha_g^* \beta_g^t\right)$$

$$s_t = \frac{\sum_g \alpha_g^t \beta_g^* \log(\alpha_g^t)}{\sum_g \alpha_g^t \beta_g^*} - \log\left(\sum_g \alpha_g^t \beta_g^*\right)$$

where α_g^* is the standardized income of educational category g for the reference year, β_g^t is the fraction of the labor force in the gth educational category in year t, and β_g^* is the value βg in the reference year. s_t can be understood as an indicator of the relative steepness of the income profiles related to education. If one fixes the fraction of the labor force in each educational group, it follows that the steeper is the income profile, the larger is the between group inequality. i_t corresponds to the Theil T index that would prevail in a population with no inequality within the educational groups and where the group incomes are proportional to the group average incomes in the base year.

Methods of Decomposition Analysis

The decomposition analysis is a useful tool for assessing the impact of certain factors on the evolution of income distribution. In general, the different decomposition methods follow two definitions (Fields 1996):

- Inequality in the population can be decomposed into different elements such that the sum of the parts is equal to total inequality.
- Inequality in the population can be decomposed as a weighted sum of inequality within and between groups.

Fields (1996) and Bourguinon, Fournier, and Gurgand (1998) employ the first method of decomposition. Fields decomposes total population inequality in a sum of different variables or elements, each being the explanatory variable in the earnings function. This helps us to answer two questions: how much income inequality is explained by each right-hand-side variable in a given point in time? And how much of the difference in inequality between groups or dates does each variable explain? This technique assumes that we know the correct model specification. Formally, this methodology can be written as Y = Z′B, where Y = ln (W) is the vector of the logarithm incomes, Z = (1, X1, …, XJ , ε) is the matrix of explanatory variables, and error term B = (α , ß1, …, ßJ,1)′ is the regression coefficient vector.
Then,

$$s_j = \frac{\mathrm{cov}(\beta_j Z_j, Y)}{\sigma^2(Y)} = \frac{\beta_j \sigma(Z_j) corr(Z_j, Y)}{\sigma(Y)} \qquad (12)$$

where sj is the relative factor weight, and ∑sj = R2 (determination coefficient).
The contribution of factor j to the change in the inequality measure I(.) between time 0 and time 1 is

$$\Delta_j[I(.)] = \frac{s'_j I'(.) - s_j I(.)}{I'(.) - I(.)}$$

, where sj is the relative weighted factor for year 0, and s′j is the relative weighted factor for year 1.
Fields also proposes a change breakdown in the factor's contribution into the following: the change in the coefficient of the factor or variable, the change of the standard deviation of the variable, and the change in the correlation between the variable and earnings.
Bourguignon, Fournier, and Gurgand (1998) decompose the effects of changes in an entire distribution rather than on a scalar summary statistic. This methodology was originally proposed by Barros and Reis (1991) and Juhn, Murphy, and Pierce (1993) and later generalized by Bourguignon, Fournier, and Gurgand.

The methodology, by means of micro simulations, decomposes the changes in income distribution into different effects. Bouillon, Legovini, and Lustig (1998) use this technique in the case of Mexico to decompose the change into the return effect, the population effect, the error term effect, and the residual effect.
This can be expressed as follows: let D(y)=D(ß, X, ε) be the income distribution measure and define y = Xß + ε, where X is the set of demographic variables, ß is the set of prices, and ε is the error terms.
If y is the income in year 0 and y′ is the income in year 1, the change in income distribution can be expressed as:

$$\Delta = D(y') - D(y) = ß(X', \varepsilon') + X(ß, \varepsilon) + \varepsilon(ß', X') + [\varepsilon (ß, X') - \varepsilon(ß', X')] \qquad (13)$$

where ß(X′, ε′) = D(ß′, X′, ε′) - D(ß, X′, ε′) is the return effect, X(ß, ε) = D(ß, X′, ε) - D(ß, X, ε) is the population effect, ε (ß′, X′) = D(ß′, X′, ε′) - D(ß′, X′, ε) is the error term effect, and [ε (ß, X′) - ε(ß′, X′)] is the residual effect.
The analysis makes the following assumptions:
Income is correctly expressed as a linear combination.
In order to compute D(ß, X′, ε), the residuals in the second year are rescaled to the second year of reference by a constant such that the variance in that year is the same as the variance of the residuals in the first year. This, in turn, implies that the distribution of ε and ε′ just differs by the variance.
Bouillon, Legovini, and Lustig (1998, 1999) use this methodology. In these documents, although the assumption of unchangeable dispersions of the regression error terms does not significantly restrict the model's results, using the variance instead of a proper inequality index is questionable. This means that one measure is used for the within inequality, and another is used for the between inequality.
Miguel Székely (1995), in order to explain the inequality changes between two points in time, applies the following formula:

$$C_B(\pi) = \frac{T'_B(\pi) - T_B(\pi)}{T' - T} \qquad (14)$$

where π is the partition or division of the population, T′B(π) is the Theil index between groups in year 1, TB(π) is the Theil index between groups in year 0, CB(π) is the percentage of the change in inequality explained by the variables in π, T′ is the Theil index in year 1, and T is the Theil index in year 0.
This methodology does not allow us to separate the income from the allocation effect.

Annex 3. Evolution of Inequality

Table 3A.1. Decomposition of Total Current Income

Income source	Gini coefficient by income source	Share in total income	Gini correlation with total income rankings	Contribution of total income to Gini coefficient	Percentage share in overall Gini
1984					
Earnings	0.6428	0.4688	0.7249	0.2184	46.0
Monetary income excluding earnings	0.7568	0.3191	0.6470	0.1562	32.9
No monetary current income	0.6067	0.2120	0.7750	0.0997	21.0
Total	0.4744	1.0000	1.0000	0.4744	100.0
1989					
Earnings	0.6128	0.4635	0.7562	0.2148	41.0
Monetary income excluding earnings	0.8185	0.3109	0.7410	0.1886	36.0
No monetary current income	0.6541	0.2256	0.8187	0.1208	23.0
Total	0.5242	1.0000	1.0000	0.5242	100.0
1992					
Earnings	0.6440	0.4541	0.7790	0.2278	42.9
Monetary income excluding earnings	0.8129	0.2848	0.7316	0.1694	31.9
No monetary current income	0.6079	0.2611	0.8449	0.1341	25.2
Total	0.5313	1.0000	1.0000	0.5313	100.0
1994					
Earnings	0.6690	0.4932	0.8123	0.2680	50.2
Monetary income excluding earnings	0.7948	0.2550	0.6827	0.1384	25.9
No monetary current income	0.6051	0.2518	0.8365	0.1274	23.9
Total	0.5338	1.0000	1.0000	0.5338	100.0
1996					
Earnings	0.6514	0.4725	0.7870	0.2422	46.7
Monetary income excluding earnings	0.7924	0.2802	0.6884	0.1529	29.4
No monetary current income	0.6026	0.2472	0.8325	0.1240	23.9
Total	0.5192	1.0000	1.0000	0.5192	100.0

Source: Authors’ estimates based on ENIGH.

Table 3A.2. Pearson Correlation among Explanatory Variables

Year and variable	Education	Occupation	Economic sector	Status
1988				
Education	1.00			
Occupation	0.64	1.00		
Economic sector	0.08	0.10	1.00	
Status	0.05	0.06	-0.04	1.00
Spearman's rhoa	0.58			
1992				
Education	1.00			
Occupation	0.63	1.00		
Economic sector	0.06	0.02	1.00	
Status	0.08	0.08	-0.04	1.00
Spearman's rhoa	0.60			
1997				
Education	1.00			
Occupation	0.64	1.00		
Economic sector	0.09	0.04	1.00	
Status	0.11	0.09	-0.06	1.00
Spearman's rhoa	0.62			

a. Spearman's correlation between education and occupation.
Source: Authors' calculation based on ENEU Survey.

Table 3A.3. Ratio of Income Share of the Highest 10 Percent to the Lowest 40 Percent of Household Income Distribution

Low-income countries a	Ratio	High-income countries a	Ratio	Latin American countriesb	Ratio
China	1.6	Australia	1.7	Argentina	2.8
Egypt	1.3	Belgium	1.0	Bolivia	3.6
India	1.4	Canada	1.4	Brazil	5.6
Côte d'Ivoire	1.6	France	2.1	Chile	4.4
Kenya	4.7	Germany	1.3	Costa Rica	2.5
Madagascar	2.2	Italy	1.4	Ecuador	4.9
Nigeria	2.4	Japan	1.0	El Salvador	3.5
Pakistan	1.2	New Zealand	1.8	Mexico	4.4
Sri Lanka	1.1	Spain	1.0	Panama	4.9
Tanzania	1.7	Sweden	1.0	Paraguay	5.7
Uganda	2.0	Switzerland	1.8	Peru	2.6
Vietnam	1.5	United Kingdom	1.9	Uruguay	2.2
Zimbabwe	4.6	United States	1.6	Venezuela	2.7

a. World Bank (1996).
b. IDB (1998 -1999).

References

Abadie, Alberto (1997), "Changes in Spanish Labor Income Structure during the 1980's: A quantile Regression Approach". Investigaciones Económicas, vol. 21, num. 2, pp.253-272.

Altimir, Oscar., and S. Piñera (1982). "Análisis de descomposición de las desigualdades de ingreso en la América Latina." *Trimestre Económico* 49(196):813–60.

Barros, Ricardo, and José Guilherme Almeida Reis (1991) "Wage Inequality and the Distribution of Education: A Study of the Evolution of Regional Differences in Inequality in Metropolitan Brazil." *Journal of Development Economics* 36:117–43.

Bouillon, Cesar, Arianna Legovini, and Nora Lustig (1998) "Rising Inequality in Mexico: Returns to Household Characteristics and the Chiapas Effect." IADB.

——— (1999) "Can Education Explain Income Inequality Changes in Mexico?" IADB.

Bourguignon, François (1979). "Decomposable Income Inequality Measures." *Econometrica* 47(4):901–20.

Bourguignon, François, Martin Fournier, and Marc Gurgand (1998). "Labor Incomes and Labor Supply in the Course of Taiwan's Development, 1979–1994." The World Bank. Mimeo.

Buchinsky, Moshe (1994) Changes in the U.S. Wage Structure 1963-1987: Application of Quantile Regression". Econometrica, vol. 62, num. 2, pp. 405-458.

——— (1995), "Quantile Regression, Box-Cox transformation model and the U.S. wage structure, 1963-1987". Journal of Econometrics, vol. 65, pp. 109-154.

———.(1998), "Recent Advances in Quantile Regression Models: A Practical Guideline for Empirical Research". Journal of Human Resources, vol.33, num 1, pp.88-126.

Burfisher, Mary E., Robinson, Sherman, and Thierfelder (1993) "Wage Changes in a U.S.-Mexico Free Trade Area: Migration Versus Stolper–Samuelson Effects." Working Paper 645.

University of California, Berkeley, Department of Agricultural and Resources Economics. Processed.

Cowell, F (1980) “On the Structure of Additive Inequality Measures.” *Review of Economic Studies* 47: 521–31.

Cragg, Michael, and Mario Epelbaum. (1996) “Why Has the Wage Dispersion Grown in Mexico? Is It the Incidence of Reforms or the Growing Demand for Skills?” *Journal of Development Economics* 51, vol. 47, 99–116.

De la Torre, Rodolfo (1997) “Desigualdad, pobreza y polarización social en México, Processed.

Elías, Víctor J. (1992). “Sources of Growth: A Study of Seven Latin American Economies.” International Center for Economic Growth. Processed.

Feenstra, Robert C., and Gordon H. Hanson (1996) “Globalization, Outsourcing, and Wage Inequality.” *AEA Papers and Proceedings* 86(2):240–45.

Fields, Gary S (1996) “Accounting for Income Inequality and Its Change.” Cornell University. Paper prepared for presentation at the American Economic Association annual meetings, New Orleans, La. Processed.

Fiszbein, Ariel (1991) *An Essay on Labor Markets and Income Inequality in Less Developed Countries.* Ph.D. diss. University of California, Berkeley.

Hanson, H. Gordon (1997) “Increasing Returns, Trade, and the Regional Structure of Wages.” *Economic Journal* 107(440):113–33.

Hanson, H. Gordon, and Ann Harrison (1995) “Trade, Technology, and Wage Inequality.” Working Paper 5110. National Bureau of Economic Research, Cambridge, Mass. Processed.

Hernández Laos, Enríque, Nora Garro Bordonaro, and Ignacio Llamas Huitrón. (1997)

"Productividad y mercado de trabajo en México." Processed.

IDB (Interamerican Development Bank). Informe (1998 – 1999) "América Latina frente a la Desigualdad: Progreso Económico y Social en América Latina."

Johnson, George E (1997) "Changes in Earnings Inequality: The Role of Demand Shifts." *Journal of Economic Perspectives* 11(2, spring):41–54.

Juhn, Chihui, Kevin Murphy, and Brooks Pierce (1993) "Wage Inequality and the Rise in Returns to Skill." *Journal of Political Economy* 3(3):410–48.

Knight, J. T., and R. H. Sabot (1983) "Educational Expansion and the Kuznets Effect." *American Economic Review* 73:1132–36.

Leibbrandt, M. V., Chrisopher D. Woolard, and Ingrid D. Woolard (1996) "The Contribution of Income Components to Income Inequality in South Africa." Living Standards Measurement Study. Working Paper 125. World Bank, Washington, D.C. Processed.

Londoño, Juan Luis (1996) "Poverty, Inequality, and Human Capital Development in Latin America, 1950–2025." World Bank, Latin American and Caribbean Studies, Washington, D.C. (June). Processed.

Lustig, Nora, and Miguel Székely (1996). "Mexico: Evolución económica, pobreza y desigualdad.". Mimeo.

Meza, Liliana. (1999). " Cambios en la estructura salarial en Mexico en el periodo 1988-1993 y el aumento en el rendimiento de la educacion superior", *Trimestre Económico* 49(196):813–60.

Montenegro, Claudio E. (1998) "The structure of Wages in Chile 1960-1996: An Approach of Quantile Regressions." Economics Letters, vol. 60 num. 2, pp. 229-235.

Moreno, A. (1989) "La distribución del ingreso laboral urbano en Colombia: 1976–1988."

Desarrollo y Sociedad (Bogotá), num. 24.

Muller, Richard E. (1998) "Public-Private Sector Wage Differentials in Canada: Evidence from Quantile Regressions." Economics Letters, vol. 60, num 2, pp. 229-235.

Pánuco-Laguette, Humberto, and Miguel Székely (1996) "Income Distribution and Poverty in Mexico." In Victor Bulmer-Thomas, ed., *The New Economic Model in Latin America and Its Impact on Income Distribution and Poverty,* pp. 185–222. New York: St. Martin's Press.

Psacharopoulos, George (1993) "Returns to Investment in Education: A Global Update." Policy Research Paper 1067. World Bank, Policy Research Department, Washington, D.C. (January). Processed.

Psacharopoulos, George, S. Morley, Albert Fiszbein, H. Lee, and B. Wood (1992) "Poverty and Income Distribution in Latin America: The Story of the 1980s." World Bank, Washington, D.C. Processed.

Ramos, Lauro (1990) *The Distribution of Earnings in Brazil: 1976–1985*. Ph.D. diss., University of California, Berkeley.

Ramos, Lauro, and C. Trindade (1992) "Educação e desigualdade de salários no Brasil: 1977/89." In *Perspectivas da Economia Brasileira 1992.* Rio de Janeiro: IPEA .

Reis, José Guilherme Almeida, and Ricardo Barros (1989) "Um estudo da evolução das diferenças regionais da desigualdade no Brasil." Rio de Janeiro, IPEA. Processed.

Reyes, A. (1988) "Evolución de la distribución del ingreso en Colombia." *Desarrollo y Sociedad*, num 21.

Rodríguez, J. (1991) "Desigualdad salarial y educación en Lima Metropolitana: 1970 a 1984." Master's thesis. PUC/RJ, Rio de Janeiro.

Schultz, T. Paul. (1988) "Education Investments and Returns." In Hollis Chenery and T. N. Srinivasan, eds., *Handbook of Development Economics,* vol. I, pp. 543–629. Elsevier Science Publishers B.V.

Shorrocks, A. F. (1980) "The Class of Additively Decomposable Inequality Measures." *Econometrica* 48(3):613–25.

———(1984) "Inequality Decomposition by Factor Components." *Econometrica* 52(6):1369–84.

Shorrocks, A. F., and J. E. Foster (1985) "Transfer Sensitive Inequality Measures." *Review of Economic Studies* 5:105–38.

Shorrocks, A. F., and D. Mookherjee. (1982) "A Decomposition Analysis of the Trend in U.K. Income Inequality." *Economic Journal* 92:886–902.

Shultz and Mwabu. (1996) "Symposium Issue on How International Exchange, Technology, and Institutions Affect Workers." 1997. *The World Bank Economic Review* 11 (1, January).

"Symposium on Wage Inequality." (1997). *Journal of Economic Perspectives* 11(2, spring).

Székely, Miguel. (1995) "Aspectos de la desigualdad en México." *Trimestre Económico* LXII (246):201–43.

Tan, Hong, and Geeta Batra. (2000) "Technology and Firm Size-Wage Differentials in Colombia, Mexico, and Taiwan (China)." *The World Bank Economic Review* 11(1):59–83.

Vieira, M. L. P. (1998) "A relação entre educação e desigualdade no Brasil." Master's diss. EPGE , Rio de Janeiro.

World Bank. (1996) *World Development Report 1996*. Washington, D.C.: Oxford University Press.