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EDUCATION AND INCOME DISTRIBUTION: NEW EVIDENCE FROM CROSS-COUNTRY DATA*

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Abstract

This paper presents empirical evidence on how education is related to income distribution in a panel data set of a broad range of countries for a period between 1960 and 1990. The findings indicate that education factors - higher attainment and more equal distribution of education - play a significant role in making income distribution more equal. The result also confirms the Kuznets inverted-U curve for the relationship between income level and income inequality. We also find that government social expenditure contributes to more equal distribution of income. However, a significant proportion of cross-country and over-time variations of income inequality still remain unexplained. Simulation exercises on income distribution show that growth of income and education on their own cannot make income distribution more equal in the short and medium term.

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1. INTRODUCTION

Income distribution has long been a topic of persistent interest among economists. Initially, attention was focused on whether inequality is necessary for accumulation and how income distribution changes with economic growth. In recent years, motivated by the availability of new data sets and advances in the theory of economic growth and development, there has been renewed interest in understanding the determinants and dynamics of income distribution.[1] Perhaps for this reason Atkinson's presidential address at the Royal Economic Society was titled "Bringing income distribution in from the cold."

The literature emphasizes education as one of the major factors affecting the degree of income inequality. Policymakers usually justify higher educational spending as a very effective tool for reducing income inequality. However, theoretical studies suggest that the relation between education and income inequality is not always clear. For instance, the human capital model of income distribution, stemming from the work of Schultz, Becker and Mincer, implies that the distribution of earnings (or income) is determined by the level and distribution of schooling across the population. While the model predicts an unambiguous positive association between educational inequality, measured by the variance of schooling, and income inequality, the effect of increased average schooling on income distribution may be either positive or negative, depending on the evolution of rates of return to education. Knight and Sabot (1983) also emphasize the complicated effect of human capital accumulation on income distribution by "composition" and "wage compression" in a dual economy. They argue that an expansion of education has two different effects on the earnings distribution. The "composition" effect increases the relative size of the group with more education and tends initially to raise income inequality, but eventually to lower it. On the other hand, the "wage compression" effect decreases the premium on education as the relative supply of educated workers increases, thereby lowering income inequality.

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[1] See Atkinson (1997), Acemoglu (1997), Becker and Tomes (1986), Benabou (1994), Deininger and Squire (1996a, 1996b), Durlauf (1996), Galor and Zeira (1993), Galor and Tsiddon (1997), and Gotschalk and Smeeding (1997), among others.

Consequently, the effect of increased education on the dispersion of income is ambiguous.

The purpose of this paper is to investigate the relationship between education and income distribution. Considering the ambiguous theoretical predictions on the relation between education and income distribution, we look for empirical evidence based on a cross-country data set. There are a number of empirical studies that have investigated the relationship between education and income equality (see a survey by Psacharopoulos and Woodhall (1985, pp.264-270) and Ram (1989)). Earlier work shows that there is a close relation between education and income distribution in developed countries. Becker and Chiswick (1966) show that, across regions in the United States, income inequality is positively correlated with inequality in schooling and negatively correlated with the average level of schooling. Chiswick (1971), based on cross-section data from nine countries, suggests that earnings inequality increases with educational inequality. Subsequent studies are based on a slightly larger sample of countries. Most of them find that a higher level of schooling reduces income inequality, while inequality of educational attainment increases it (Adelman and Morris (1973), Chenery and Syrquin (1975), Ahluwalia (1975), Marin and Psacharopoulos (1974), Psacharopoulos (1977) and Winegarden (1987)). On the other hand, Ram (1984 and 1989) finds, with slightly different specifications and data, that mean schooling and schooling inequality do not have any statistically significant effects on income inequality.

Previous cross-national studies are very much hampered by a lack of internationally comparable data, and end up with few data points from heterogeneous sources. The quality of data on income distribution and schooling has always been questioned. Unlike previous empirical studies, our paper utilizes a panel data set, of internationally comparable human capital and income distribution, for a broad number of countries measured at five-year intervals from 1960 to 1990. Data on income distribution has been compiled by Deininger and Squire (1996a) and in the form of a time series, at irregular frequencies, for more than 100 countries since 1960. Measures of the level of schooling and its inequality are constructed from the Barro and Lee (1996) education attainment data set for more than 100 countries at five-year intervals from 1960. Based on this unbalanced panel data set, we investigate both cross-national and intertemporal relationships between education and income distribution.

In the next section we discuss the data and present the results of estimating the effects of education and income on income distribution. In section 3 we analyze the determinants of educational level and its inequality across countries, based on past values of educational variables and income. In section 4 we provide an assessment of our results, by decomposing the cross-section differences in income distribution, and we provide some quantitative estimates of the long-term effects of changes in education on income distribution. Section 5 presents the conclusions.

2. THE EFFECTS OF EDUCATION ON INCOME DISTRIBUTION

Income distribution is related to the population's average schooling and its dispersion. Income inequality increases with education inequality. In contrast, for a given distribution of education, an increase in average schooling has an ambiguous effect on income distribution.

To illustrate this, traditional models of human capital theory would suggest the following expression for the level of earnings (*Y*) of an individual with *S* years of schooling:

$$\log Y_s = \log Y_o + \sum_{j=1}^{s} \log(1+r_j) + u,$$

where r_j is the rate of return to the *j*th year of schooling. The function can be approximated by:

$$\log Y_s = \log Y_o + rS + u.$$

The distribution of earnings can be written as:

$$Var(\log Y_s) = Var(rS) = \bar{r}^2 Var(S) + \bar{S}^2 Var(r) + 2\bar{r}\bar{S}Cov(r,S).$$

Hence, an increase in educational inequality (Var(S)) leads unambiguously to higher income inequality, with other variables held constant. If the rate of return (*r*) and schooling level (*S*) are independent, an increase in the level of schooling will also lead unambiguously to a more unequal income distribution. If, however, the covariance between the return to education and the level of education is negative (as evidenced by a number of studies by Psacharopoulos), an increase in schooling can reduce income inequality. For example, we can think of an economy where improved access to education may allow people with high abilities to earn more income than people with low abilities, even when all of them have the same level of education (see for example, De Gregorio and Kim, (1999)). In this case, as education expands, income distribution may become more unequal.

In the rest of this section we look at the relationship between income distribution, the level and dispersion of education, and the level of income across countries. We focus on the issue of whether countries with higher educational levels or less dispersion of education among the population, or with higher levels of development, have a more equal or less equal income distribution.

Specifically, we estimate the following regression:

$$G_{j,t} = a_{0,t} + a_1 \sigma^E_{j,t} + a_2 E_{j,t} + a_3 \log y_{j,t} + a_4 [\log y_{j,t}]^2 + a_D D_j + \epsilon_{j,t}, \qquad (1)$$

where G is the Gini coefficient of income distribution. We constructed the Gini coefficients from the raw data on income share by quintile reported in Deininger and Squire (1996a). σ^E is the dispersion of education. It is calculated as the standard deviation of schooling for a given year, and based on the data constructed by Barro and Lee (1996). We refer to this variable indistinctly as distribution of education, dispersion of education, or the standard deviation of education, and use it a proxy for education inequality. E is the average years of school attainment for the population aged 15 and over, from Barro and Lee (1996). y is the level of per-capita GDP. Finally D is a set of dummy variables that distinguish certain data characteristics and regions to which countries belong. The subscripts j and t refer to country and period, respectively. The data set is an unbalanced panel for which data are available at five-yearly intervals from 1960 to 1990. The number of observations for each period t depends on the number of countries with all the data available.

To measure educational inequality, we constructed a standard deviation of educational distribution for the total population over 15 years of age. The Barro and Lee (1996) data set on educational attainment provides panel information on the distribution of population by level of educational attainment in seven categories: no formal education, incomplete primary, complete primary, first cycle of secondary, second cycle of secondary, incomplete higher, and complete higher. This information enables us to construct the standard deviation of educational distribution for each country at five-yearly intervals from 1960 to 1990.[2]

We present a summary of statistics in Table 1. It is interesting to note that, on average, educational attainment has increased since the 1960s throughout the world. Even in regions with greater inequality, such as Latin America, we see that there has been a substantial increase in average years of education. In contrast, overall inequality has increased slightly, especially in Africa. However one has to be careful when interpreting these results since for the whole world we have only 23 countries with data available in 1965, whereas we have 71 in 1990. So, what may be happening is that new data becoming available tends to be from countries with greater inequality than the pre-existing average.[3] However, the table helps to illustrate the orders of magnitude of the variables. Another interesting fact in the data is that the standard deviation of educational attainment across countries has increased in all the regions, which may be a factor offsetting the potential equalizing effect of increased educational attainment.

The regional dummies in the regressions are included to capture differences in income distribution that are not accounted for by education or income. For example, it has been argued that the distribution of landholding or natural resources are important factors explaining income distribution in Latin American countries (Londoño, 1996), and as is apparent from Table 1 there may be factors other than education that explain the differences between Latin America and Asia. We include dummies for African, Asian, and Latin American countries, since our results indicate that there is no evidence of any other significant regional dummy in equation (1).

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[2] The standard deviation is computed by assuming that each person has an educational attainment of log(1+years of schooling). Thus, a person with no formal schooling is assumed to have one (effective) year of educational human capital.

[3] This does not happen with data on education since the panel of countries is relatively balanced.

We also include some dummies to control for data characteristics. The database prepared by Deininger and Squire (1996a) uses different sources to compute Gini coefficients, depending on the data available in each country. There are three major differences. The first is whether the unit of analysis is a household or an individual. If, as is usually the case, poor households have more members, the distribution of income at a household level will be more equal than when computed at the individual level. Therefore, in our regression analysis we expect to find that the Gini coefficients are greater (more unequal income distribution) in countries that report data at the individual level. The second issue is whether income data refers to income before or after tax. Provided the tax system is progressive, countries that collect data on gross (before-tax) income will probably have a higher Gini coefficient than countries that report data on net income, and hence the dummy is presumed to have a positive coefficient. Finally, some countries measure the distribution of income, while others measure the distribution of expenditure, which is measured on the basis of net income. In addition, given that high-income households presumably save a bigger proportion of their income than poor households, it is expected that countries that use income rather than expenditure will have higher Gini coefficients.

Before going into the details of the results it is useful to look at the simple cross-correlation between income distribution and educational variables. Figure 1 plots average years of schooling (also referred to as educational attainment) in 1990 against the Gini coefficient. The relationship is negative, indicating that increases in education reduce inequality. On the other hand, Figure 2 shows that there is a positive relationship between income and educational inequality. Although these figures are suggestive, further statistical analysis is required to examine their robustness and obtain orders of magnitude for the importance of educational factors in explaining differences in income distribution across countries.

We estimate equation (1) from the panel data set of education and income distribution that we have compiled. The panel consists of 6 equations - 1965, 1970, 1975, 1980, 1985, and 1990.[4] The system is estimated by "seemingly-unrelated-regression" (SUR) techniques. This procedure allows for different error variances in each equation and for correlation of these errors across equations. We

[4] We use data from 1960 as one-period lagged explanatory variables in the regressions.

allow for different constant terms in each equation, but assume that the slope coefficients are the same for each variable. The regressions apply to a total of 274 observations.

The results are presented in Table 2. Regression 2.1 is a basic regression without regional dummy variables and without income variables. Statistical results improve in regression 2.2, which includes regional dummies. Using only contemporaneous variables, the regression explains about 70% of the variance of income distribution, except for the latter period, where its explanatory power drops below 50%.

The results show the role of education in income distribution. Countries with higher educational attainment also have more equal income distribution. Considering that the standard deviation of the cross-section of educational attainment is between 2.5 and 2.9 years, the coefficients (-0.009) suggest that an increase of one standard deviation reduces the Gini coefficient by about 0.03 (i.e. 3 percentage points), which may account for about 30% of the standard deviation of the Gini coefficient. From a country viewpoint, however, this coefficient is relatively small. The average increase in educational attainment is about 2.5 years over the last 30 years. Of course, as long as educational attainment is related to the level of income and education inequality, changes may be quantitatively more important. We discuss these issues later in the paper.

Inequality of schooling, measured as the standard deviation of educational attainment of the population, has a significantly positive effect on income inequality.[5] The estimated coefficient indicates that a reduction in educational dispersion by one standard deviation, about 0.2, reduces income inequality by 0.02. In our sample of countries, the dispersion of education has increased in average by 0.08 in the 30 year-period.

The dummy variables that distinguish certain data characteristics show that when income is measured before tax, it is more unequally distributed. This is an indication that taxes are progressive. On average, taxes reduce inequality and increase the Gini coefficient by 0.04. The dummy that

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[5] We also used other indicators of education inequality. In particular we constructed a Gini coefficient index for education inequality, and we also used an index of wage dispersion. The results were similar to those reported in the paper, although they were in general less significant.

distinguishes whether distribution refers to income rather than expenditure is in general not statistically significant, although it has a positive point estimate which indicates that expenditure is more equally distributed by 0.02. The puzzling result regarding the dummy variables is that it appears to be distributed more equally in countries where income distribution is measured at the individual level. For a sample of countries where data on income distribution is available at the individual and household levels, Deininger and Squire (1996a) show that income is indeed more equally distributed at the household level because poor households are larger. Our result comes from a different sample of countries.

With respect to regional dummies, Latin America and Africa appear to have more unequal income distribution than the world average, by about 0.1 of the Gini coefficient. In contrast, Asian countries as a region have more equal income distribution, by about 0.02 of the Gini coefficient. There exists, therefore, a large inequality gap between Latin America and Africa with respect to other countries, particularly Asia.

Regression 2.3 in Table 2 adds the log of per capita income and its square in order to capture the inverted-U curve proposed by Kuznets for the relationship between income distribution and the level of income. The results confirm that there is a Kuznets curve. We use the log of income to estimate this relationship, because the relationship was not found when measured with the level of per capita income. The Kuznets curve resulting from the regressions in Table 2 indicates that income distribution becomes more unequal with higher levels of income up to a range of income between US$ 1,800 and US$ 2,700 (PPP adjusted at 1985 international prices), and then income distribution starts equalizing.

Another specification for the Kuznets curve has been proposed by Anand and Kanbur (1993) and also estimated by Deininger and Squire (1996b). It includes income in the regression as y and $1/y$. Our results show that for different specifications the nonlinearity in the relationship between income and its distribution is significant, and it also holds when estimated for each period.[6]

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[6] To verify that the results do not depend on the variables included in the regression, nor on the period, we regress the Gini coefficients only on the income variables and time specific effects omitting

We can conclude, along similar lines to Deininger and Squire (1996b), that with cross-section data there is evidence of a Kuznets curve, but this result does not mean that the relationship is strong or holds over time. In Figure 3 we show the orthogonal component of the Gini coefficient for educational variables against per capita GDP. That is, we estimate Gini coefficients against educational inequality and attainment and the residual is plotted against the log of per capita income. The figure shows the data for 1970 and 1990 as an example. As can be seen, there is no clear evidence of a strong relationship.[7] Therefore, although the Kuznets relationship is captured in the regressions, it is rather weak.[8]

Regression 2.4 has all the independent variables lagged by one-period. The results are the same as for Regression 2.3 using contemporary variables; that is, higher education and less inequality of schooling lead to a more equal income distribution. This equation can be used to predict future income distribution from current data.

We also examine the effect of government social expenditure on income distribution. This is an important variable whose omission could bias the results on education if it is correlated with educational variables. Hence, we run Regression (1) including the ratio of social expenditure to GDP averaged over the previous five years.[9] The result is reported in column 2.5 of Table 2, and shows that government social expenditure reduces income inequality. The estimated coefficient, -0.002 (t-statistic

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all dummy variables. In Table A.1 of the appendix we report the results assuming that the relationship is the same for all the periods (Regression 1.1), and also that it is different across periods of the panel (Regressions 1.2 to 1.8). The regressions show that, with the exception of the quadratic specification using the level of income, there is evidence of a Kuznets curve.

[7] The figures are very similar for all periods and also when instead of using the orthogonal component of the Gini coefficients we use the level of the Gini coefficients.

[8] For more discussions on the Kuznets curve, see Sarel (1997) and Barro (1999).

[9] Government social expenditure is measured by the average ratio of the general government's social security and welfare expenditure to GDP over five-year sub-periods, 1970-74, 1975-79, 1980-84, 1985-89. The data, available since the early 1970s, was constructed from IMF, *Government Finance Statistics Yearbook*. We use the average ratio of 1970-74 in the regressions for Gini coefficients of 1965 and 1970.

= -1.8) implies that a one percentage-point increase in the social expenditure-GDP ratio lowers the Gini coefficient by about 0.2 percentage point. This positive contribution of government social expenditure to income equality may occur through two mechanisms. The first is that part of social expenditure consists of direct transfers to the poor, increasing their income and redistributing income from rich to poor. The second is that social expenditure may promote access for the poor to education and other human-capital enhancing activities, such as healthcare, thereby contributing to future income equality, especially when credit markets are imperfect.

Table 2 also shows three regressions for quintile shares – the share of the highest quintile, the share of the lowest quintile and the share of the middle three quintiles. The results of the Regressions 2.6, 2.7 and 2.8 show that per capita GDP has a highly significant relation to each income-share measure in nonlinear form, thus confirming the Kuznets curve. As income rises, the highest-quintile share first increases and then declines, while the shares of both the lowest quintile and the middle three quintiles first decrease and then rise with per capita income. The strong effect of government social expenditure on income distribution is also confirmed in all of the quintile share regressions. Higher social expenditure appears to lower the share of the wealthiest, while increasing the shares of the poorest and middle income groups. In contrast, the estimated effects of both education inequality and education level variables appear insignificant in these regressions for the quintile shares.

Regression 2.9 reports regressions for the log value of the average income of the lowest quintile. The results are similar to those for the lowest quintile. In particular, the regression shows that the average income of the poorest group rises with average household income.[10]

3. THE DETERMINANTS OF EDUCATION

In the previous section we examined how distribution is related to average level of educational attainment, as well as its dispersion and the level of development of the economy as measured by per

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[10] Gallop, Radelet, and Warner (1998) show that the positive relation between per capita income growth and the poorest group's income is empirically robust.

capita income. We show in that section that not only the level of education, but also how it is distributed among the population are important determinants of income distribution. Furthermore, an increase in the average level of education has an equalizing effect on income distribution.

In this section we go one step further by analyzing the evolution of education. In particular we examine how the initial level of development, together with educational characteristics, affect current educational attainment level and its dispersion. This will allow us to examine the dynamics of income distribution. In the specifications presented in this section, we focus on past income and education variables to estimate future education variables. We exclude income distribution data so as to maximize the size of the sample. In 1965, for example, we have 22 data sets with income distribution and 92 with educational variables. In fact, we have estimated the effects of income distribution on education in a smaller sample, and the results are not significantly different from those reported below. However, they are much more sensitive to changes of specification.

3.1 Evolution of Educational Attainment

In order to examine the evolution of educational attainment, we start specifying the following regression:

$$E_{j,t} = b_{0,t} + b_1 \times \sigma^E_{j,t-1} + b_2 \times \log y_{j,t-1} + b_D D_j + \epsilon_{j,t} \qquad (2)$$

The regression includes one-period lagged values of educational inequality and per capita income as explanatory variables. As it is clear from Table 1, there are strong regional differences in educational attainment, so we also include all regional dummies. The equations were estimated using SUR technique allowing for different time intercepts. The data is the five-year panel from 1965 to 1990, and because we use only income and educational data our sample contains about 90 countries.

The results of the estimation of equation (2) are shown in Table 3. Regression 3.1 implies that an increase in per capita income has a significant effect in increasing educational attainment. We find that a regional dummy for African countries has significant negative intercepts, implying that Africa is the continent of least education, by about 2.1 years, after controlling for per capita GDP. However, the other regional dummies are not statistically significant. Past education inequality also does not help to explain the level of education.

The estimated coefficient on per capita income means that a 10% increase in the level of income in period *t*-1 (5-year lagged) increases educational attainment in the next period by 0.1 years. This result also holds when a 10-year lagged value is used to measure income, so it is unlikely to be due to endogeneity problems. This result indicates that there is no convergence toward a long-run value for educational attainment. As income grows, educational attainment grows. However this effect is not very large quantitatively, as a country that is twice as wealthy as another one will have about 1 year more schooling than the lower income country.

The result of Regression 3.2, which includes past level of educational attainment, shows that educational attainment is highly persistent, and in this regression the coefficient on past educational inequality turns out to be strongly negative. Greater educational inequality tends to promote educational attainment of the population. This relationship may result if higher dispersion of education, given its initial level, results in high returns to education.

Regression 3.3 repeats Regression 3.1 with government social expenditure included as an additional explanatory variable. Social expenditure enters with a significantly positive sign, implying that greater social expenditure raises the average educational attainment of the population. However, the effect of social expenditure on education level is insignificant in regression 3.4, where past level of educational attainment is also included. Accordingly, government social expenditure seems to be correlated more closely with cross-country variations in educational attainment rather than with variations over time.

3.2 Evolution of Education Inequality

The last building block in our empirical investigation is to look at the determinants of educational inequality across countries and over time. In particular, we want to examine the relationship between past values of education and income, on the one hand, and current educational attainment on the other.

The equation is specified as follows:

$$\sigma^{E}_{j,t} = b_{0,t} + b_1 \times E_{j,t-1} + b_2 \times \log y_{j,t-1} + b_D D_j + \varepsilon_{j,t} \qquad (3)$$

The regression result of Equation (3) is presented in Table 4. Regression 4.1 shows that the main determinants of education inequality are past income and past education level. An increase in educational attainment has a significant effect in reducing education inequality. The estimated coefficient indicates that an increase of one year in average years of schooling among the working-age population is estimated to reduce the standard deviation of education by 0.016.

Initial GDP appears to have a positive relationship with education inequality, which may indicate that as a country becomes wealthier, educational inequality increases. This result would seem to conflict with the fact that increased education, which is also associated with higher income, reduces educational inequality. This may be the result of some non-linearity. Indeed, the dispersion of education would be expected either to rise or to decline with an increase in average education, depending on its initial level and distribution. Two extreme cases can be imagined: the first consists of an economy with no education at all, where an expansion of educational attainment (from zero) will mean that some people start receiving education. In this case the average level of school attainment of the population will increase, as will dispersion. The other extreme would be an economy where most people attend primary and secondary school, but only some pursue higher education. An increase in the level of educational attainment among the labor force is the result of more people attending post-secondary school, so dispersion of education is likely to decline.[11]

[11] To illustrate the nonlinear relationship between the level and the distribution of education more formally, consider that each person can have an education level between 0 and N. However, actual education is uniformly distributed between n_1 and n_2, where $0<n_1<n_2<N$. Therefore n_2 is the years of school attainment of the most educated part of the population, while n_1 is the minimum years of school attainment in such economy. Given the distributional assumption, the mean of educational attainment, E, is equal to $(n_2+n_1)/2$ and the standard deviation of educational attainment, σ^E, is $(n_2-n_1)/12^{0.5}$. Clearly, regardless of whether n_1 or n_2 increase, E unambiguously increases. However, an increase in n_1 reduces the standard deviation of school attainment, while an increase in n_2 raises it. An (additive) increase of the same magnitude in both, n_1 and n_2, leaves σ^E unchanged. Which case is more likely?

Accordingly, the impact of an expansion of education on its dispersion must depend on its initial level. For this reason we add to equation (3) a square term on E_{t-1}, resulting in the following equation:

$$\sigma^{E}_{j,t} = b_{0,t} + b_1 \times E_{j,t-1} + b_2 \times E^{2}_{j,t-1} + b_3 \times \log y_{j,t-1} + b_D D_j + \varepsilon_{j,t} \qquad (4)$$

The impact of a marginal increase in E_{t-1} on σ^E is $b_1 + 2b_2\, E_{t-1}$, and we expect this to be positive negative) for low (high) values of E; thus, we presume that $b_1 > 0$ and $b_2 < 0$. Indeed an initial confirmation of presumption is presented in Figure 4, where panel (A) and panel (B) plot the dispersion of education against average educational attainment for the two extreme periods of our panel, and it is clear from the figure that, at low levels of education, its expansion causes an increase in dispersion, whereas for higher levels the relationship is reversed. The figures show that this reversion occurs between 3 and 5 years of schooling.[12]

Regression 4.3 adds the squared education term to the basic regression, and the result confirms our presumption and the evidence of Figure 4. According to the coefficient estimates, the point at which education becomes dispersion-reducing is 4.2 years.[13]Moreover, Regression 4.3 shows that the coefficient on per capita income becomes insignificantly different from zero when the square of educational attainment is included. The explanatory power of the regression increases substantially compared to 4.1 once the square of education is added.

Regression 4.3 has the same specification plus a lagged dependent variable. The result shows that the dispersion of education is highly persistent over time. In this case, the non- linearity coefficients

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We think that when n_1 and n_2 are both low, in the limiting case equal to zero, expansion of education occurs because of increases in n_2, therefore increasing educational dispersion. When n_2 reaches N, further increases in average education, in our example, are produced by increases in n_1, and therefore, education inequality declines.

[12] The graphs are very similar when current educational attainment is used in the horizontal axis.

[13] In a previous version we used a different specification for non-linearity using an interaction term between E and its lagged value, and the results also showed a cutoff at about 3.5 years.

on per capita income change sign, but they are not important in the relevant range, as they imply that educational dispersion decreases with attainment up to 12 years, which is outside the values in our sample. The coefficients on the regional dummy variables for Africa, Asia, and Latin America also change signs across specifications. Their inclusion does not affect the main results, but increases the R^2.

Regressions 4.4 and 4.5 include government social expenditure as an explanatory variable. The coefficients on social expenditure appear negative, implying that higher social expenditure helps to decrease the inequality of schooling among the population. However, the estimated coefficient is statistically insignificant in Regression 4.5, which includes the inequality of past schooling. In summary, we find that government social expenditure helps to explain cross-country differences in income distribution, level of educational attainment and dispersion of education.

4. ASSESSMENT

In the previous section we estimated the determinants of education and income distribution. In this section we use our estimates to explain cross-country differences in income distribution and to explore the dynamic implications of our results.

4.1 Explaining differences in income distribution

We use the empirical result of Regression 2.5 to determine the relative contribution of each of the explanatory variables to income distribution in 1990 for 49 countries for which all necessary data are available. Appendix Table A.2 shows the results in a framework of "sources of income distribution" to show how the explanatory variables account for each country's income distribution relative to the mean value for all the sample countries. Thus, this exercise looks at cross-section differences in income distribution. The 10 most equal countries in the upper quintile of income distribution include five OECD countries (Spain, Finland, Belgium, Canada, Netherlands), four Asian countries (Bangladesh, Sri Lanka, Taiwan, Pakistan) and one Africa/Middle East country (Egypt). The 10 most unequal countries include five African countries (Zimbabwe, Guinea-Bissau, Kenya, Mali, South Africa) and five Latin

American ones (Chile, Panama, Brazil, Mexico, Guatemala). Thus, income distribution differs systematically across regions and this is why regional dummies appear very significant in the regressions. Nonetheless, we find that education and income factors played a moderate role in explaining the variations across countries. For example, in the five most equal OECD countries as listed in Appendix Table A.2, the mean Gini coefficient was below the world average by 0.137; 0.020 of this gap was explained by education factors (including educational attainment and education inequality) and 0.040 by income factors. Social expenditure also contributed to lower income inequality by 0.020, which leaves an unexplained gap of 0.057. For the most unequal five African countries, the mean Gini coefficient was 0.158 higher than the world average; education factors accounted for 0.020, while income and social expenditure explained 0.006 and 0.008 respectively. Thus, the bulk of the inequality in the most unequal countries cannot be explained by educational factors, government social expenditure or income. As income level has a nonlinear relationship with income distribution inequality, the lower income in the African countries does not contribute much to income inequality, compared to countries in other developing regions.

The cross-section accounting of national differences in income distribution grouped by regions is presented in Table 5. The average Gini coefficient for African countries was 0.062 higher than the world average in 1990, and the regression explains a difference of 0.061. Because African countries had a higher education inequality and more importantly, a lower level of education, their Gini coefficient was predicted to be higher by 0.019. Lower income and lower social expenditure in Africa also contributed to higher income inequality by 0.003 and 0.007 respectively.

The effect of income levels on regional differences in inequality is more visible in Latin America and OECD countries. In Latin America, which has a Gini coefficient 0.096 higher than the average, 0.005 of this difference is attributed to the difference in education factors, 0.032 to the difference in income and 0.005 to the difference in social expenditure. In OECD countries education and income factors accounted for 0.020 and 0.041 respectively, out of a total difference of 0.081. Higher social expenditure in OECD countries also explained about 0.015 of the difference. Between regions, in Asia neither education nor income significantly explain the relative equality of income distribution.

The main conclusion from this exercise is that income and education factors are important in explaining the cross-section differences in income distribution, although we cannot explain the bulk of the differences by these factors alone.

4.2 Dynamic Implications

Our empirical results in Sections 2 and 3 may be used to explain the evolution of income distribution over time and explore some dynamic implications. The question we want to examine is how much and for how long do changes in education and income affect income distribution.

Using equations 2.5, 3.2 and 4.1, we can simulate the evolution of education and its dispersion, and income distribution. Following the values of Table 1 we consider a "typical" developing country around 1990, with income per capita of US$ 3,000 (1985 prices), a Gini coefficient of 0.45, 5 years of educational attainment and 0.9 years of education dispersion among the population, and a rate of growth of per capita income of 2.5%. The question is then what will happen to education and income distribution in the future, over a 25-year horizon.

The simulations are presented in Table 6. Considering only the effects of growth at a rate of 2.5% per year, the Gini coefficient only drops from 0.450 to 0.428, which is not very big change for such a long period of time. Since education also expands with the level of income, the result is that at the end of 25 years the level of education attainment reaches 5.6 years. We are not considering the effects of higher educational attainment on higher income since we assume an exogenous growth rate.

If this country were to increase average schooling by one and half years exogenously, in addition to growing at 2.5%, due, for example, to an aggressive policy to expand education[14], the Gini coefficient will drop to 0.424. The partial effect of education is very small. Hence, although the effects appear statistically significant in the regressions, they are quantitatively small once we take into account the interactions with education inequality. Indeed, as Table 6 illustrates, the increase in educational attainment increases educational dispersion. We also consider the effect of an increase in social

[14] Of course this is an extreme assumption because policies are unlikely to produce such a change in a period of 5 years, but it helps to quantify an extreme case.

expenditure by one standard deviation, and the partial effect also appears to be small.

In contrast to the previous results for education and social expenditure, rapid growth may bring a faster reduction in inequality. If the growth rate doubles to 5.0%, the Gini coefficient drops to 0.384, which amounts to a decline of 15% in income inequality. Again, the addition of a strong expansion of education and social expenditure would contribute to a decline in inequality, by a small magnitude. The growth effect explains the bulk of the reduction in inequality.

We conclude that the expansion of education does not produce a significant decline in income inequality, since part of the effects are offset by the increase in educational inequality. Therefore, from a policy perspective, an educational policy seeking to influence income inequality should not only concentrate on increasing the years of education, but also on reducing its dispersion.

The other issue is how education and income distribution have evolved in each country over time. While we showed that income distribution across countries is clearly accounted for by differences in education, we have found that the variation of income distribution for each country over time is not clearly explained by education and income factors alone. This is because actual changes in education and income within countries were quite large over the decades, while changes in income inequality were relatively small over time. Therefore, while our results may help to understand better why countries show persistent differences in income distribution, the stability of income distribution over time must be explained by other factors. This is exactly what our simulations show: the interplay between income, education and its distribution does not produce significant changes over time.

5. CONCLUDING REMARKS

In searching for explanations, one interesting issue is why income distribution differs so much across countries and between regions, and how some countries have been so successful in reducing inequality in recent years. By understanding the major determinants of income distribution, we may discover policy implications that would help to reduce inequality. This paper looks closely at one of the main determinants of income distribution, namely education. Policy makers usually argue that efforts in the educational field may reduce income inequality.

This paper provides empirical evidence on how education and income have related to income distribution in a panel data set of a broad range of countries for a period from 1960 to 1990. We have also analyzed the effects of social expenditure. The findings indicate that education factors - higher attainment and more equal distribution of education - play some role in changing income distribution. The result confirms the Kuznets inverted-U curve for the relationship between income level and income inequality. We also find that government social expenditure contributes to a more equal distribution of income.

However, we should emphasize that a significant proportion of cross-country and over-time variations of income inequality still remain unexplained. Simulation exercises show that the expansion of income and education alone cannot make income inequality decline substantially in a short period. The significance of the regional dummies for Africa and Latin America indicates that income distribution in the countries of these regions has been systematically less equal than in the countries of other regions. Some recent studies have examined the effects of macroeconomic factors on income distribution (De Gregorio (1995), Sarel (1997), Bulír (1998) and Li, Squire and Zou (1998)), but they do not account for all educational factors we have examined in this paper. We plan to explore the connections between income distribution, education, macroeconomic factors, and government policy.

The small quantitative effects of educational expansion on income distribution are due in part to the impact of educational expansion on the inequality of educational attainment in the population. Therefore, a policy to expand education needs to focus closely on the inequality of education if the aim is to reduce income inequality.

Table 1: Summary of data

	Average 1965	Standard deviation 1965	Average 1990	Standard deviation 1990
School Attainment	***E***	F^E	***E***	F^E
Mean	3.86	0.73	5.58	0.81
Standard deviation	2.58	0.19	2.83	0.19
Maximum	9.91	1.10	11.7	1.19
Minimum	0.17	0.32	0.65	0.36
Africa				
Mean	1.61	0.74	2.81	0.88
Standard deviation	1.06	0.18	1.40	0.16
Asia				
Mean	2.96	0.85	5.24	0.89
Standard deviation	1.87	0.19	2.56	0.13
Latin America				
Mean	3.51	0.85	5.43	0.81
Standard deviation	1.29	0.19	1.59	0.13
OECD				
Mean	6.66	0.55	8.44	0.59
Standard deviation	2.25	0.15	1.98	0.15

	Average 1965	Average 1990
Gini coefficient	***G***	***G***
Mean	0.368	0.411
Standard deviation	0.090	0.101
Maximum	0.560	0.623
Minimum	0.229	0.233
*Africa**		
Mean	0.462	0.460
Standard deviation	0.127	0.097
Asia		
Mean	0.379	0.367
Standard deviation	0.079	0.075
*Latin America**		
Mean	0.517	0.498
Standard deviation	0.063	0.067
OECD		
Mean	0.354	0.327
Standard deviation	0.088	0.050

* The first period is 1970 because of data availability.

Table 2: Panel Regressions for income distribution

Dependent Variable	*Gini Coefficient*				
	2.1	2.2	2.3	2.4	2.5
Educ. inequality (F^E)	0.044	0.097	0.058	0.047	0.014
	(0.032)	(0.027)	(0.028)	(0.027)	(0.032)
Educ. attainment (E)	-0.018	-0.009	-0.008	-0.008	-0.006
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
log of per capita GDP			0.284	0.270	0.454
			(0.085)	(0.082)	(0.096)
Square of log of per capita GDP			-0.018	-0.018	-0.029
			(0.005)	(0.005)	(0.006)
Social Expenditure/GDP(%)(t-1)					-0.0021
					(0.0012)
Data dummies:					
Individual (vs. house)	-0.014	-0.032	-0.034	-0.037	-0.027
	(0.010)	(0.008)	(0.008)	(0.008)	(0.009)
Gross Income (vs. net)	0.058	0.041	0.041	0.046	0.037
	(0.012)	(0.010)	(0.010)	(0.010)	(0.011)
Income (vs. expenditure)	0.020	0.019	0.016	0.018	0.023
	(0.016)	(0.013)	(0.013)	(0.013)	(0.014)
Regional dummies:					
Africa		0.095	0.105	0.105	0.090
		(0.015)	(0.017)	(0.018)	(0.019)
Asia		-0.021	-0.021	-0.028	-0.032
		(0.013)	(0.015)	(0.015)	(0.016)
Latin America		0.103	0.093	0.089	0.074
		(0.012)	(0.012)	(0.012)	(0.014)
R^2's (number of observations)	0.40 (22)	0.52 (22)	0.49 (21)	0.49 (21)	0.48 (18)
	0.51 (39)	0.74 (39)	0.74 (39)	0.80 (37)	0.71 (31)
	0.51 (46)	0.70 (46)	0.73 (46)	0.71 (45)	0.74 (36)
	0.48 (48)	0.76 (48)	0.76 (48)	0.75 (48)	0.61 (42)
	0.32 (54)	0.62 (54)	0.63 (54)	0.64 (54)	0.77 (48)
	0.33 (65)	0.58 (65)	0.59 (63)	0.59 (65)	0.49 (64)

Notes: Standard errors in parentheses. For regressions (2.1)-(2.5), the dependent variable is the Gini coefficient at five year intervals from 1960 to 1990, i.e., 1965, 1970, 1975, 1980, 1985 and 1990. For regressions (2.6), (2.7) and (2.8), the dependent variables are the share of the highest quintile, the share of the middle three quintiles and the share of the lowest quintile. Regression (2.9) uses the log value of the average income of the lowest quintile as the dependent variable. The system of equations was estimated by the seemingly-unrelated-regression (SUR) techniques. Different constant terms (not reported) are included in each equation. Regression 2.4 uses one-period lagged values for education attainment, education inequality and per capita income variables.

Table 2(continued): Panel Regressions for income distribution.

Dependent Variable	*Income Share* Highest quintile	Middle three quintiles	Lowest quintile	*Average Income* of lowest quintile (log)
	2.6	2.7	2.8	2.9
Educ. Inequality	0.024	-0.026	0.005	0.238
	(0.031)	(0.025)	(0.009)	(0.170)
Educ. attainment	-0.003	0.003	-0.001	0.005
	(0.003)	(0.002)	(0.001)	(0.344)
log of per capita GDP	0.367	-0.311	-0.076	-0.469
	(0.105)	(0.084)	(0.028)	(0.546)
Square of log of per	-0.024	0.020	0.005	0.093
capita GDP	(0.007)	(0.005)	(0.002)	(0.034)
Social Expenditure /GDP(%) (t-1)	-0.0025 (0.0011)	0.0018 (0.0009)	0.0008 (0.0003)	0.013 (0.006)
Data Dummies				
Individual (vs house)	-0.032	0.021	0.013	0.225
	(0.001)	(0.007)	(0.003)	(0.053)
Gross Income (vs. net)	0.014	-0.007	-0.009	-0.142
	(0.011)	(0.009)	(0.003)	(0.056)
Income (vs. Expend.)	0.025	-0.022	-0.007	-0.122
	(0.014)	(0.011)	(0.004)	(0.070)
Regional dummies				
Africa	0.088	-0.074	-0.016	-0.380
	(0.019)	(0.011)	(0.005)	(0.095)
Asia	-0.018	0.009	0.011	0.152
	(0.015)	(0.012)	(0.004)	(0.079)
Latin America	0.087	-0.066	-0.018	-0.406
	(0.014)	(0.011)	(0.004)	(0.074)
R^2 (number of)	0.58(16)	0.58(16)	0.01(18)	0.90(16)
observations)	0.71(27)	0.73(27)	0.55(27)	0.90(27)
	0.74(29)	0.71(29)	0.65(29)	0.96(29)
	0.57(39)	0.54(39)	0.50(39)	0.91(39)
	0.67(42)	0.69(42)	0.62(42)	0.96(42)

	0.70(43)	0.71(43)	0.69(43)	0.95(43)

Table 3: Regressions for educational attainment

Dependent variable	*Average years of schooling*			
	3.1	3.2	3.3	3.4
Educ. attainment (*E*) (t-1)		0.945 (0.009)		0.944 (0.011)
Educ. inequality (F^E) (t-1)	-0.010 (0.308)	0.276 (0.080)	0.338 (0.352)	0.395 (0.102)
log of per capita GDP (t-1)	0.975 (0.113)	0.130 (0.030)	1.481 (0.120)	0.151 (0.038)
Social Expenditure/GDP(%) (t-1)			0.107 (0.022)	-0.0003 (0.005)
Regional dummies:				
Africa	-2.147 (0.331)	-0.145 (0.055)	-0.762 (0.333)	-0.109 (0.067)
Asia	-0.064 (0.443)	0.083 (0.055)	1.113 (0.437)	0.086 (0.064)
Latin America	-0.516 (0.388)	-0.103 (0.042)	0.124 (0.295)	-0.135 (0.050)
R^2(number of observations)	0.50 (92)	0.99 (92)	0.53 (65)	0.99 (65)
	0.52 (93)	0.95 (93)	0.57 (66)	0.93 (66)
	0.54 (98)	0.98 (98)	0.58 (68)	0.98 (68)
	0.55 (103)	0.96 (103)	0.69 (90)	0.95 (90)
	0.59 (105)	0.99 (105)	0.71 (94)	0.99 (94)
	0.62 (106)	0.98 (106)	0.69 (80)	0.98 (80)

Note: Standard errors in parentheses.

Table 4. Regressions for schooling Inequality

Dependent variable	*Education Inequality (Standard Deviation)*				
	4.1	4.2	4.3	4.4	4.5
Educ. inequality (F^E)			0.898		0.883
(t-1)			(0.014)		(0.020)
Educ. attainment (E)	-0.016	0.066	-0.025	0.061	-0.024
(t-1)	(0.005)	(0.010)	(0.004)	(0.011)	(0.004)
Square of Ed. Attainment		-0.008	0.0011	-0.007	0.0010
(E^2) (t-1)		(0.001)	(0.0003)	(0.001)	(0.0003)
log of per capita GDP	0.045	0.014	0.006	-0.018	0.007
(t-1)	(0.014)	(0.013)	(0.004)	(0.016)	(0.005)
Social				-0.011	-0.0009
Expenditure/GDP(%) (t-1)				(0.002)	(0.0006)
Regional dummies:					
Africa	0.063	0.066	-0.031	-0.066	-0.028
	(0.037)	(0.032)	(0.008)	(0.033)	(0.008)
Asia	0.201	0.130	-0.017	-0.019	-0.021
	(0.045)	(0.038)	(0.008)	(0.036)	(0.008)
Latin America	0.101	0.029	-0.019	-0.060	-0.023
	(0.038)	(0.032)	(0.006)	(0.028)	(0.007)
R^2 (number					
of observations)	0.14 (92)	0.34 (92)	0.95 (92)	0.40 (65)	0.96 (65)
	0.14 (93)	0.31 (93)	0.89 (93)	0.39 (66)	0.88(66)
	0.17 (98)	0.38 (98)	0.94 (98)	0.52 (68)	0.94(68)
	0.18 (103)	0.39 (103)	0.90 (103)	0.46 (90)	0.89(90)
	0.18 (105)	0.46 (105)	0.96 (105)	0.57 (94)	0.96(94)
	0.14 (106)	0.48 (106)	0.96 (106)	0.61 (80)	0.96(80)

Note: Standard errors in parentheses.

Table 5: Explaining cross-country differences of income distribution in 1990

	Africa	Asia	Latin America	OECD
Gini (1990)*				
Actual	0.062	-0.033	0.096	-0.081
Predicted	0.061	-0.030	0.087	-0.081
Explained by				
Education	0.019	0.001	0.005	-0.020
Educational attainment	0.018	-0.000	0.004	-0.017
Educational inequality	0.001	0.001	0.001	-0.003
Income	0.003	0.015	0.032	-0.041
Social Expenditure	0.007	0.009	0.005	-0.015
Other Factors**	0.032	-0.055	0.044	-0.005

* Differences from the mean value of Gini coefficients for a sample of 49 countries in 1990. The list of the countries and the same type of accounting for each individual country are shown in table A.2 of the Appendix.

** Other factors include data characteristics and regional dummy.

Table 6: Simulations

	Gini Coeff.	Educational Attainment	Educational Dispersion	Income per capita
C Initial in 1990	0.450	5.0	0.900	3000
25 years later				
C Growth of 2.5%.	0.428	5.37	0.701	5561
C Growth of 2.5% and 1.5 year increase in educational attainment.	0.424	6.26	0.890	5561
C Growth of 2.5%, 1.5 year increase in educational attainment,and one std. deviation increase in social expenditure.	0.421	6.64	0.878	5561
C Growth of 5.0%.	0.384	6.19	0.690	10159
C Growth of 5.0% and 1.5 year increase in educational attainment.	0.382	7.09	0.884	10159
C Growth of 2.5%, 1.5 year increase in educational attainment,and one std. deviation increase in social expenditure.	0.377	7.46	0.873	10159

Source: Author’s calculations.

Figure 1: Educational Attainment and Income Distribution, 1990

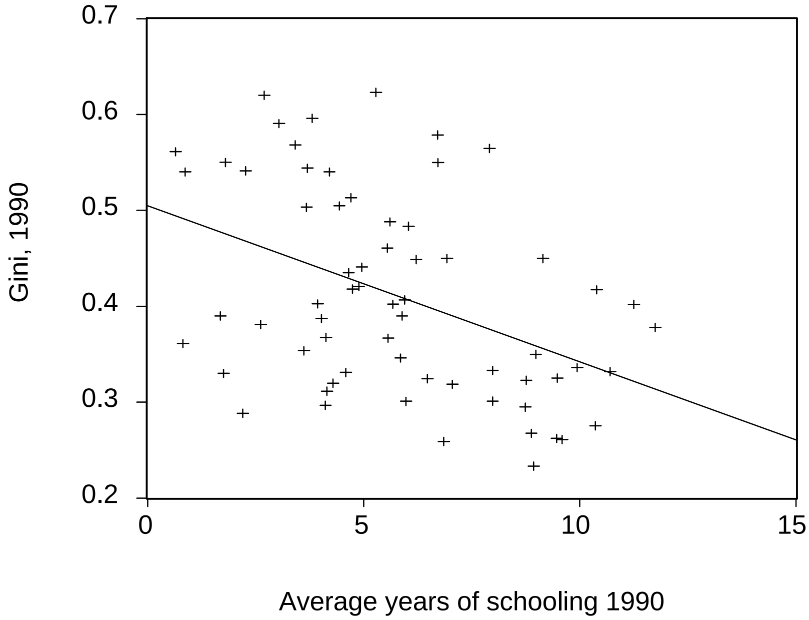


Figure 2 Education Dispersion and Income Distribution, 1990

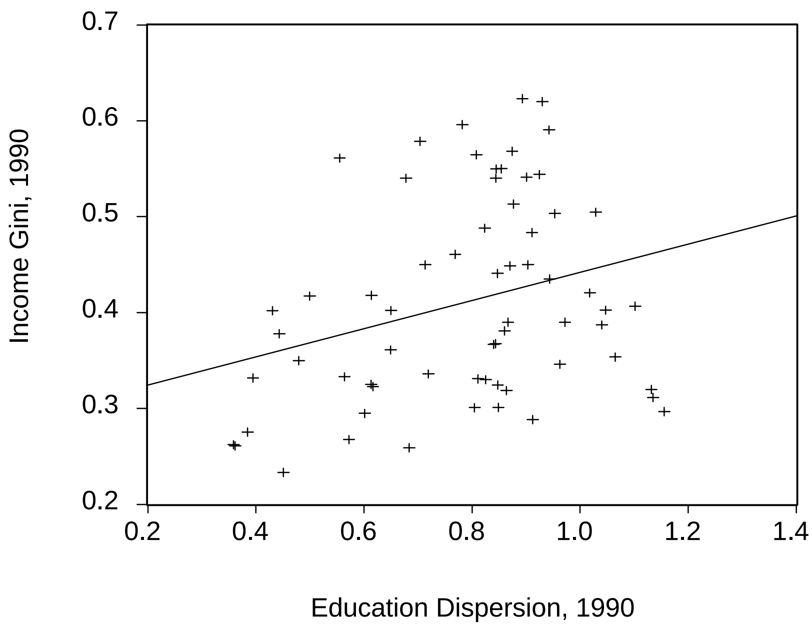
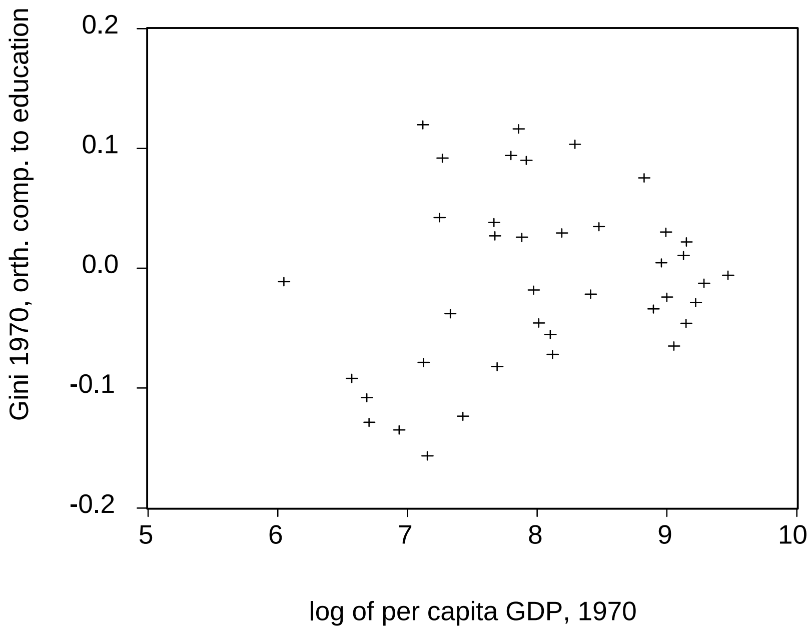


Figure 3: Kuznets Curves

(A)



(B)

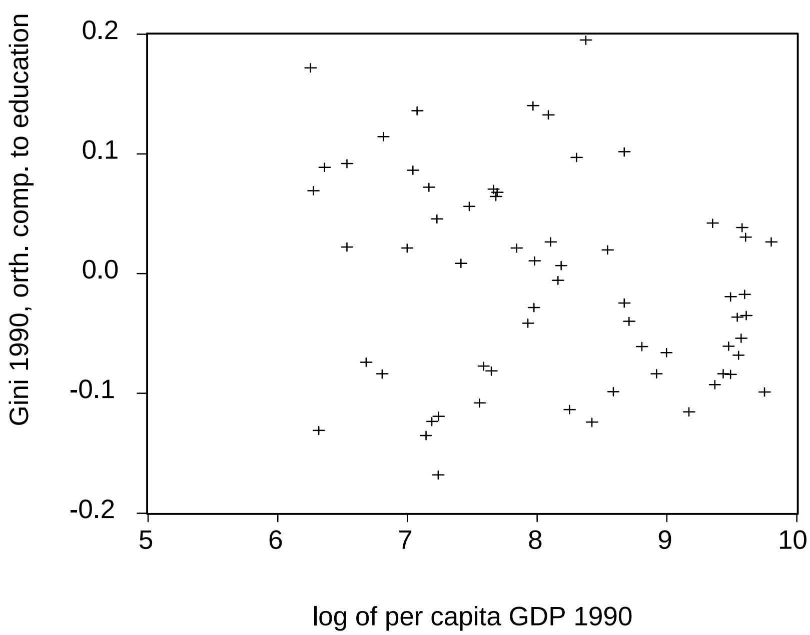
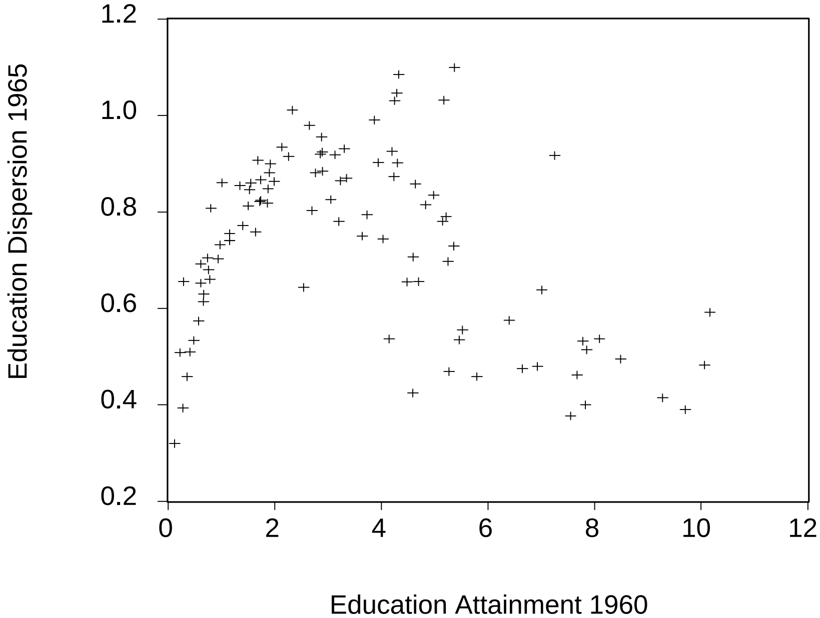
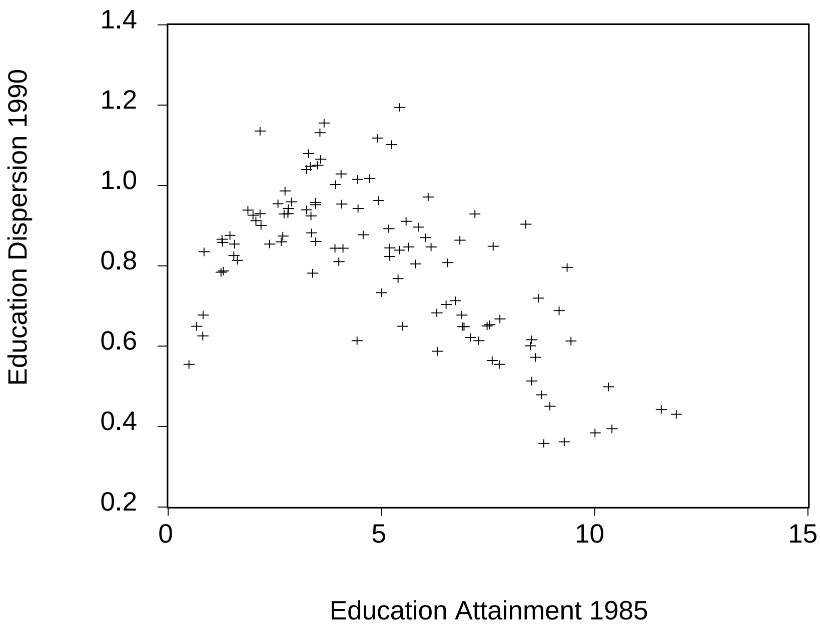


Figure 4: Education Inequality and Education Attainment

(A)



(B)



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APPENDIX

Table A.1: Regressions for Kuznets curve

- Dependent variable is the Gini coefficient

	Regression number and period							
	1.1 1965-90	1.2 1960	1.3 1965	1.4 1970	1.5 1975	1.6 1980	1.7 1985	1.8 1990
Indep. Vars.								
I. Log-specification								
log gdp*	0.447	1.304	0.488	0.798	0.714	0.616	0.529	0.236
	(0.113)	(0.416)	(0.341)	(0.260)	(0.203)	(0.208)	(0.192)	(0.168)
[log gdp]^2	-0.030	-0.085	-0.033	-0.052	-0.047	-0.040	-0.034	-0.016
	(0.007)	(0.026)	(0.021)	(0.016)	(0.013)	(0.013)	(-0.012)	(0.010)
II. Square-specification								
gdp**	-0.98	8.85	-5.43	1.32	0.89	-0.66	-0.89	-0.26
	(0.49)	(25.4)	(16.9)	(1.56)	(1.04)	(9.20)	(0.80)	(-0.81)
[gdp]^2 ***	1.29	-27.8	-5.15	-22.1	-16.2	-2.76	0.57	-2.53
	(3.33)	(27.2)	(16.1)	(13.6)	(8.08)	(6.36)	(5.29)	(4.99)
III. Anand-Kanbur specification								
gdp**	-1.11	-3.52	-1.55	-2.02	-1.73	-1.45	-1.18	-0.73
	(0.20)	(0.96)	(0.70)	(0.54)	(0.37)	(0.32)	(0.29)	(0.27)
1/gdp	-40.9	-159.8	-48.3	-88.5	-77.3	-71.0	-70.0	-7.78
	(19.1)	(63.5)	(51.8)	(38.7)	(34.4)	(43.7)	(39.6)	(29.8)

Standard errors in parenthesis.

* gdp corresponds to per capita GDP.

** Coefficient is multiplied by 10^{-5}.

*** Coefficient is multiplied by 10^{-10}.

Table A.2, Sources of Cross-country Differnces in Income Distribution, 1990

Country	Actual Gini	Predicted gini	Explained by Education	Income	Social Expe.	Other
SPAIN	-0.150	-0.074	-0.005	-0.012	-0.017	-0.039
FINLAND	-0.148	-0.099	-0.026	-0.046	-0.010	-0.016
BELGIUM	-0.141	-0.108	-0.019	-0.040	-0.032	-0.016
CANADA	-0.133	-0.083	-0.031	-0.067	-0.006	0.021
BANGLADESH	-0.120	-0.034	0.026	0.030	0.009	-0.098
NETHERLANDS	-0.114	-0.105	-0.018	-0.039	-0.032	-0.016
SRI LANKA	-0.108	-0.053	0.002	0.039	0.005	-0.098
TAIWAN	-0.108	-0.081	-0.010	0.000	0.004	-0.075
PAKISTAN	-0.097	-0.043	0.017	0.030	0.009	-0.098
EGYPT	-0.089	-0.012	0.016	0.038	0.000	-0.066
U.K.	-0.086	-0.116	-0.018	-0.040	-0.015	-0.043
ITALY	-0.084	-0.072	-0.001	-0.035	-0.020	-0.016
SWEDEN	-0.084	-0.118	-0.022	-0.051	-0.028	-0.016
UGANDA	-0.079	0.017	0.027	-0.026	-0.008	0.024
INDONESIA	-0.078	-0.039	0.010	0.038	0.011	-0.098
DENMARK	-0.077	-0.079	-0.032	-0.045	-0.022	0.021
NORWAY	-0.076	-0.098	-0.014	-0.052	-0.016	-0.016
KOREA,SOUTH(R)	-0.073	-0.014	-0.023	0.012	0.009	-0.011
JAPAN	-0.059	-0.045	-0.021	-0.048	0.004	0.021
GHANA	-0.055	0.062	0.019	0.010	0.010	0.024
MAURITIUS	-0.042	0.050	0.005	0.019	0.003	0.024
PORTUGAL	-0.041	-0.008	0.013	0.005	-0.010	-0.016
U.S.A.	-0.031	-0.094	-0.038	-0.073	-0.004	0.021
SINGAPORE	-0.019	-0.026	0.004	-0.029	0.010	-0.011
GAMBIA	-0.019	0.064	0.028	0.002	0.010	0.024
NEW ZEALAND	-0.007	-0.058	-0.035	-0.027	-0.016	0.021
GUYANA	-0.007	0.031	0.001	0.020	0.002	0.008
TUNISIA	-0.006	-0.007	0.017	0.039	0.003	-0.066
AUSTRALIA	0.008	-0.063	-0.029	-0.049	-0.005	0.021
BOLIVIA	0.012	0.062	0.011	0.035	0.009	0.008
ZAMBIA	0.026	0.036	0.012	-0.009	0.010	0.024
VENEZUELA	0.032	0.102	0.008	0.017	0.009	0.068
PERU	0.040	0.059	0.001	0.039	0.011	0.008
PHILIPPINES	0.041	-0.007	-0.005	0.036	0.011	-0.048
HONG KONG	0.041	-0.070	-0.016	-0.052	0.009	-0.011
COSTA RICA	0.052	0.112	0.004	0.037	0.004	0.068
MALAYSIA	0.075	-0.002	0.003	0.025	0.009	-0.038
THAILAND	0.079	0.039	0.004	0.036	0.010	-0.011
DOMINICAN REP.	0.096	0.093	0.014	0.039	0.009	0.031
MALI	0.131	0.031	0.030	-0.030	0.007	0.024
KENYA	0.135	0.062	0.017	0.010	0.011	0.024
MEXICO	0.141	0.091	-0.002	0.019	0.006	0.068
GUINEA-BISS	0.152	0.055	0.030	-0.009	0.010	0.024
PANAMA	0.156	0.099	-0.010	0.039	0.002	0.068
ZIMBABWE	0.159	0.073	0.018	0.023	0.008	0.024
CHILE	0.170	0.043	-0.004	0.031	-0.014	0.031
GUATEMALA	0.182	0.138	0.021	0.039	0.010	0.068

BRAZIL	0.187	0.126	0.014	0.033	0.011	0.068
SOUTH AFRICA	0.214	0.163	0.007	0.038	0.008	0.111

Note: * Gini is the difference of gini coefficients from the mean value of all 49 countries.
** Other factors include data characteristics and regional dummies.