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EDUCATION AND INCOME INEQUALITY: NEW EVIDENCE FROM CROSS-COUNTRY DATA

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This paper presents empirical evidence on how education is related to income distribution in a panel data set covering a broad range of countries for the period between 1960 and 1990. The findings indicate that educational factors—higher educational attainment and more equal distribution of education—play a significant role in making income distribution more equal. The results also confirm 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 variation in income inequality remains unexplained.

1. INTRODUCTION

Income distribution has long been a topic of 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 theories of economic growth and development, there has been renewed interest in understanding the determinants and the dynamics of income distribution.[1] It is no surprise, then, that the title of Anthony Atkinson's presidential address at the Royal Economic Society in 1996 was "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 highly 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

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[1]See Atkinson (1997), Acemoglu (1997), Becker and Tomes (1986), Benabou (1994), Deininger and Squire (1996, 1998), Durlauf (1996), Galor and Zeira (1993), Galor and Tsiddon (1997), and Gottschalk and Smeeding (1997), among others.

that the distribution of earnings (or income) is determined by the level and the distribution of schooling across the population. While the model predicts an unambiguously positive association between educational inequality, as measured by the variance of schooling, and income inequality, the effect of increased average schooling on income inequality may be either positive or negative, depending on the evolution of rates of return to education.

In the literature on development economics, Knight and Sabot (1983) also emphasize the complicated effect of human capital accumulation on income distribution due to "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. 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 about the relation between education and income distribution, we look for empirical evidence based on a cross-country data set. A number of empirical studies have investigated the relationship between education and income equality (see the survey by Psacharopoulos and Woodhall, 1985, pp. 264–70; Ram, 1989). Earlier work shows 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), using cross-sectional data from nine countries, suggests that earnings inequality increases with educational inequality. Subsequent studies have been 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.[2] On the other hand, Ram (1984, 1989) finds, with slightly different specifications and data, that mean schooling and schooling inequality have no statistically significant effects on income inequality.

Previous cross-national studies are very much hampered by a lack of internationally comparable data, and they therefore end up with a 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 newly constructed 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 have been compiled by Deininger and Squire (1996) 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) educational attainment data set for more than 100 countries at five-year

[2]Adelman and Morris (1973), Chenery and Syrquin (1975), Ahluwalia (1976), Marin and Psacharopoulos (1976), and Winegarden (1979).

intervals from 1960. Using 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 inequality. 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 assess our results by decomposing the cross-sectional differences in income inequality, and we provide some quantitative estimates of the long-term effects of changes in education on income distribution. Section 5 presents our conclusions.

2. The Effects of Education on Income Inequality

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 and u reflects other factors that influence earnings independent of education. The function can be approximated by

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

Using a bar over a variable to denote its mean, we can write the distribution of earnings as

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

Hence, an increase in educational inequality ($\mathrm{Var}(S)$) leads unambiguously to greater 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 ability to earn more income than people with low ability, even when all of them have the same level of education.[3] In this case, as education expands, income distribution may become more unequal. This may be particularly important in economies with very low levels of education. However, as more people receive education, the return on education will decline, reducing income inequality.

[3] See, for example, De Gregorio and Kim (2000).

In the rest of this section we look at the relationship among income inequality, 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.

We estimate the following regression[4,5]:

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

where G is the Gini coefficient, a measure of the distribution of income. We constructed Gini coefficients from the raw data on income share by quintile reported in Deininger and Squire (1996). The variable σ^E is the dispersion of educational attainment in the population. It is calculated as the standard deviation of schooling for a given year and is based on the data constructed by Barro and Lee (1996). We refer to this variable as the distribution of education, the dispersion of education, or the standard deviation of education, and we use it as a proxy for educational inequality. E is the average years of school attainment for the population aged 15 and over, from Barro and Lee (1996). The variable y is GDP per capita. Finally, D is a set of dummy variables that distinguish certain data characteristics and regions to which countries belong. The subscripts j and t index countries and periods, respectively. The data set is an unbalanced panel for which data are available at five-year intervals from 1960 to 1990.[6] 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 attainment for each country at five-year intervals from 1960 to 1990.[6]

We present a summary of statistics in Table 1. On average, since the 1960s, educational attainment has increased 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 it may be that new data

[4]One concern in the empirical specification is that any effect of education (as well as of income) on income distribution may reflect reverse causation, that is, income inequality affecting educational attainment. We try to control for this endogeneity problem by using lagged rather than contemporaneous values of the independent variables in the estimation of equation (1). See the results of Regression 2.3 in Table 2.

[5]We also test whether the level and the dispersion of education have any nonlinear relationship with income inequality. However, the squares of educational attainment and inequality turned out to be statistically insignificant in the regressions for income inequality.

[6]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.

TABLE 1

SUMMARY OF DATA

School Attainment	Average E 1965	Standard Deviation s^E 1965	Average E 1990	Standard Deviation s^E 1990
All countries				
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

Gini Coefficient	Average 1965	Average 1990
All countries		
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

Note: *The first period is 1970 because of data availability.

becoming available tend to be from countries with greater inequality than the previous average.[7] Another interesting observation is that the standard deviation of educational attainment across countries has increased in all 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

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

example, it has been argued that the distribution of landholding and the distribution of 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).

We also include some dummies to control for data characteristics. The database prepared by Deininger and Squire (1996) 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 than more affluent households, the distribution of income at the household level will be more equal than that computed at the individual level. Therefore, in our regression analysis we expect to find that the Gini coefficients are greater (income distribution is more unequal) in countries that report data at the individual level. The second issue is whether income data refer 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 larger 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 inequality and the 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 on education and income distribution that we have compiled. The panel consists of six equations: for 1965, 1970, 1975, 1980, 1985, and 1990.[8] The system is estimated by ''seemingly-unrelated-regression'' (SUR) techniques.[9] This procedure allows for different

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

[9]The SUR estimation identifies relationships using both cross-country variations and within-country time-series variation. Since there is little within-country time-series variation in measured income inequality, the estimated results are mostly driven by cross-sectional relationships. The panel estimation including country fixed effects (not reported here) confirms that there is no significant relationship between educational and income inequality. The relationship between educational inequality and income inequality also becomes insignificant if we use balanced panel data, mainly because the sample size of the balanced panel data becomes very small, covering only 15 countries in each period of the panel from 1965 to 1990. By contrast, the cross-sectional relationship between educational inequality and income inequality for each period of the panel turns out to be statistically significant for most single periods (results available from the authors on request).

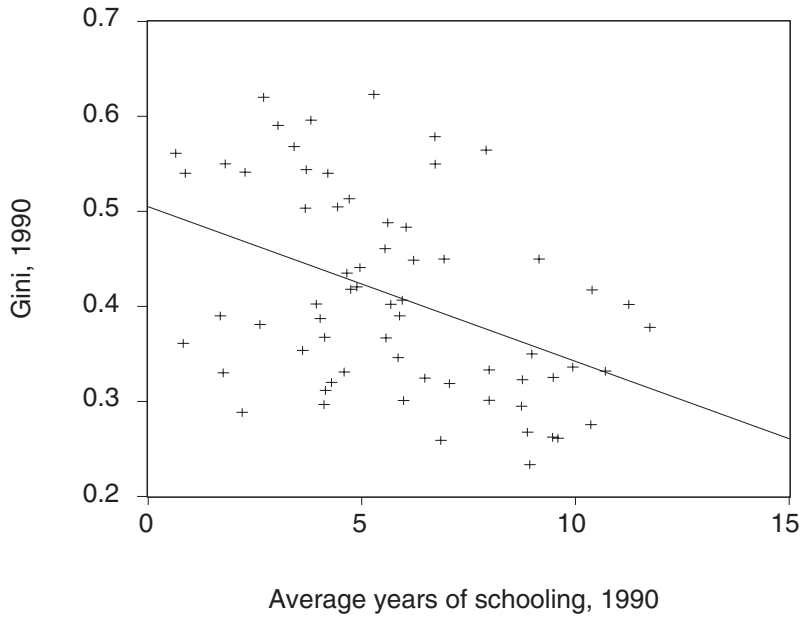

Figure 1. Educational Attainment and Income Distribution, 1990

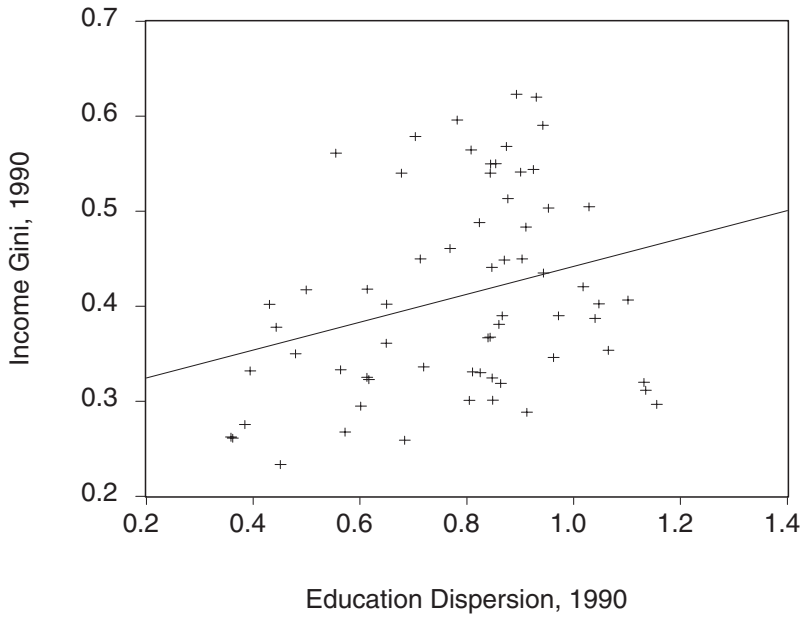

Figure 2. Education Dispersion and Income Distribution, 1990

TABLE 2

PANEL REGRESSIONS FOR INCOME INEQUALITY

	Gini Coefficient			
Dependent Variable	2.1	2.2	2.3	2.4
Educational inequality (σ^E)	0.097	0.058	0.047	0.014
	(0.027)	(0.028)	(0.027)	(0.032)
Educational attainment (E)	–0.009	–0.008	–0.008	–0.006
	(0.002)	(0.003)	(0.003)	(0.003)
Log of GDP per capita		0.284	0.270	0.454
		(0.085)	(0.082)	(0.096)
Square of log of GDP per capita		–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. household)	–0.032	–0.034	–0.037	–0.027
	(0.008)	(0.008)	(0.008)	(0.009)
Gross income (vs. net)	0.041	0.041	0.046	0.037
	(0.010)	(0.010)	(0.010)	(0.011)
Income (vs. expenditure)	0.019	0.016	0.018	0.023
	(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 (number of obs.)	0.52 (22)	0.49 (21)	0.49 (21)	0.48 (18)
	0.74 (39)	0.74 (39)	0.80 (37)	0.71 (31)
	0.70 (46)	0.73 (46)	0.71 (45)	0.74 (36)
	0.76 (48)	0.76 (48)	0.75 (48)	0.61 (42)
	0.62 (54)	0.63 (54)	0.64 (54)	0.77 (48)
	0.58 (65)	0.59 (63)	0.59 (65)	0.49 (64)

Note: The system has six equations, where the dependent variable is the Gini coefficient at five-year intervals from 1965 to 1990. The system of equations was estimated by the seemingly unrelated regression (SUR) technique. The estimation allows for different error variances in each equation and for correlation of these errors across equations. Different constant terms (not reported) are included in each equation. Standard errors are reported in parentheses. The R^2 and number of observations apply to each equation. Regression 2.3 uses one-period-lagged values for the educational attainment, educational inequality, and income per capita variables.

error variances in each equation and for correlation of these errors across equations. We allow for different constant terms in each equation, but we assume that the slope coefficients are the same for each variable across equations.[10] The regressions apply to a total of 274 observations.

The results are presented in Table 2. Regression 2.1 is a basic regression without income variables. Using only contemporaneous education and other controlling variables, the regression explains about 70 percent of the variance of

[10]We test the restrictions on the slope coefficients for each explanatory variable across equations in Regression 2.2, reported in Table 2. A test of equality for all six coefficients for educational inequality is accepted by a Wald test at a p-value of 0.57. The p-value for the test of equality of the coefficient on educational attainment is 0.07. For income per capita and its square terms, the joint test of equality of estimated coefficients is accepted at a p-value of 0.13.

income distribution, except for the latter period, where its explanatory power drops below 50 percent.

The results show the role of education in income inequality. Countries with higher educational attainment also have a 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 in educational attainment reduces the Gini coefficient by about 0.03 (that is, 3 percentage points), which may account for about 30 percent 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 past 30 years. In addition, as long as educational attainment is related to the level of income and educational 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.[11] 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 on average by 0.08 over the 30-year period.

The dummy variables that distinguish certain data characteristics show that, when income is measured before taxes, it is more unequally distributed. This is an indication that taxes are indeed progressive. On average, taxes reduce inequality and decrease the Gini coefficient by 0.04. The dummy that 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 than income by 0.02. The puzzling result regarding the dummy variables is that expenditure 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 are available at the individual and the household levels, Deininger and Squire (1996) show that income is indeed more equally distributed at the household level because poor households tend to be larger. Our result comes from a different sample of countries.

With respect to regional dummies, Latin America and Africa appear to have greater income inequality than the world average, by about 0.1 of the Gini coefficient. In contrast, the Asian countries as a group have a 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 2.2 in Table 2 adds the log of income per capita 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 (Kuznets, 1995). The results confirm that a Kuznets curve also exists in these panel data. We use the log of income to estimate this relationship, because no relationship was found when the measured level of income per capita was used as a regressor. The Kuznets curve

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

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 (in purchasing power parity-adjusted dollars at 1985 international prices) and then starts to equalize.

Another specification for the Kuznets curve has been proposed by Anand and Kanbur (1993) and estimated by Deininger and Squire (1998). 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.[12,13]

We can conclude, along lines similar to Deininger and Squire (1998), that with cross-sectional 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 to educational variables against GDP per capita. That is, we estimate Gini coefficients against educational inequality and attainment, and the residual is plotted against the log of income per capita. 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.[14] Therefore, although the Kuznets relationship is captured in the regressions, it is rather weak.[15]

Regression 2.3 includes all the independent variables lagged by one period to control for the possible endogeneity problem. The results are the same as for Regression 2.2 using contemporaneous variables; that is, higher educational attainment 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 2.1 including the ratio of social expenditure to GDP averaged over the previous five years.[16] The result, reported in column 2.4 of Table 2, shows that government

[12]To verify that the results do not depend on the variables included in the regression, or on the period, we regressed the Gini coefficients on the income variables and time-specific effects only, omitting all dummy variables. In Table A.1 of the Appendix we report the results assuming that the relationship is the same for all periods (Regression 1.1) and, alternatively, 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.

[13]When we perform regressions for quintile shares—the share of the highest quintile, the share of the lowest quintile, and the share of the middle three quintiles—GDP per capita has a highly significant relation to each income-share measure in nonlinear form, thus confirming the Kuznets curve. As GDP per capita increases, the highest-quintile share first increases and then declines, while the shares of both the lowest quintile and the middle three quintiles decrease initially and then rise. We also find that the average income of the poorest quintile rises with average household income. All of those results are reported in the working paper version of this paper (De Gregorio and Lee, 1999). Gallop, Radelet, and Warner (1998) show that the positive relation between growth in income per capita and the poorest group's income is empirically robust.

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

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

[16]Government social expenditure is measured by the average ratio of general government social security and welfare expenditure to GDP over five-year subperiods: 1970–74, 1975–79, 1980–84, and 1985–89. The data, available from the early 1970s, were constructed from International Monetary Fund, *Government Finance Statistics Yearbook*. We use the average ratio of 1970–74 in the regressions for Gini coefficients of 1965 and 1970.

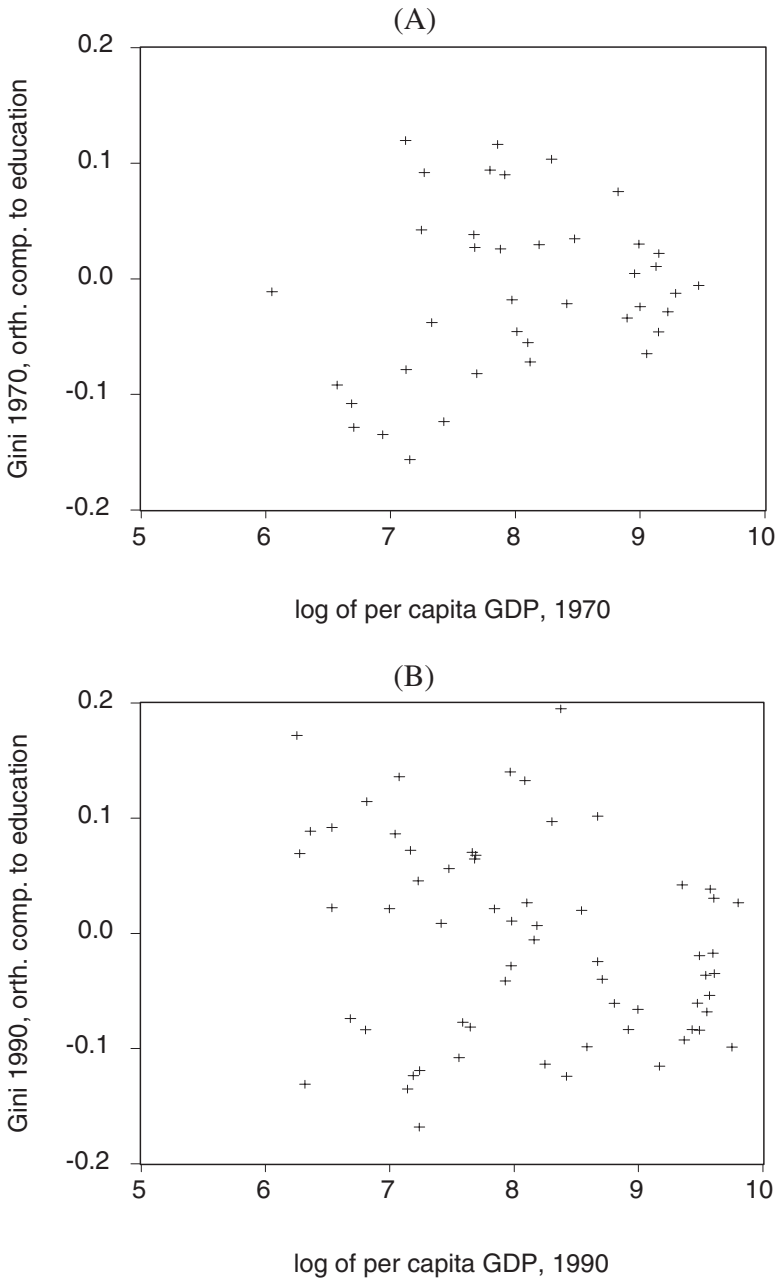

Figure 3. Kuznets Curves

social expenditure reduces income inequality. The estimated coefficient, –0.002 (*t*-statistic = –1.8), implies that a 1-percentage-point increase in the social expenditure-GDP ratio lowers the Gini coefficient by about 0.2 percentage points. 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.[17] The second is that social expenditure may promote access for the poor to education and other human-capital-enhancing activities, such as health care, thereby contributing to future income equality, especially when credit markets are imperfect.

3. The Determinants of Education

In the previous section we examined how distribution is related to the average level of educational attainment, as well as its dispersion and the level of development of the economy as measured by income per capita. We showed in that section that not only the level of education, but also how it is distributed among the population, is an important determinant 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, affects current educational attainment and its dispersion. This will allow us to examine the dynamics of income distribution.[18] In the specifications presented in this section, we focus on past income and educational variables to estimate future educational variables.[19]

3.1. *Evolution of Educational Attainment*

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

$$(2) \quad E_{j,t} = b_{0,t} + b_1 E_{j,t-1} + b_2 \sigma^E_{j,t-1} + b_3 \log y_{j,t-1} + b_4 [\log y_{j,t-1}]^2 + b_D D_j + v_{j,t}.$$

The regression includes one-period-lagged values of educational inequality and income per capita and the lagged dependent variable as explanatory variables. We also include income per capita squared as a regressor.[20] As is clear from Table 1, there are strong regional differences in educational attainment, so we also include all regional dummies. The equations were also estimated using the SUR technique allowing for different time intercepts. The data are those in the five-year panel from 1965 to 1990, and because we use only income and educational data, our sample contains about 90 countries.

[17]The regressions for quintile shares show that higher social expenditure lowers the share of the wealthiest, while increasing the shares of the poorest and the middle-income groups.

[18]We do not fully investigate the factors that determine the level and dispersion of educational attainment, because our main interest is in explaining the interaction between education and income variables. We control for the possible endogeneity problem by using one-period-lagged independent variables in the regressions.

[19]We exclude the income inequality variable so as to maximize the size of the sample. In 1965, for example, we have data on income inequality for 22 countries and data on educational variables for 92. In fact, we have estimated the effects of income inequality on educational variables in a smaller sample, and the results are not significantly different from those reported here. However, they are much more sensitive to changes in specification.

[20]The square of log income per capita turns out to be statistically insignificant, so it is excluded.

TABLE 3

REGRESSIONS FOR EDUCATIONAL ATTAINMENT

	Average Years of Schooling			
Dependent Variable	3.1	3.2	3.3	3.4
Educational attainment $(E)(t-1)$		0.710		0.948
		(0.254)		(0.011)
Educational inequality $(\sigma^E)(t-1)$	–0.085	0.222	0.278	0.337
	(0.305)	(0.083)	(0.353)	(0.106)
Log of GDP per capita $(t-1)$	3.830	0.710	2.421	0.658
	(0.910)	(0.254)	(1.099)	(0.314)
Square of log of GDP per capita $(t-1)$	–0.184	–0.038	–0.060	–0.033
	(0.057)	(0.016)	(0.069)	(0.021)
Social expenditure/GDP $(t-1)$			0.108	–0.001
			(0.022)	(0.005)
Regional dummies				
Africa	–2.251	–0.126	–0.758	–0.084
	(0.331)	(0.054)	(0.334)	(0.068)
Asia	–0.237	0.082	1.096	0.087
	(0.452)	(0.054)	(0.438)	(0.063)
Latin America	–0.794	–0.122	0.066	–0.147
	(0.399)	(0.042)	(0.300)	(0.050)
R^2 (number of obs.)	0.50 (92)	0.99 (92)	0.53 (65)	0.99 (65)
	0.51 (93)	0.95 (93)	0.56 (66)	0.94 (66)
	0.54 (98)	0.98 (98)	0.58 (68)	0.98 (68)
	0.54 (103)	0.96 (103)	0.68 (90)	0.95 (90)
	0.58 (105)	0.99 (105)	0.71 (94)	0.99 (94)
	0.60 (106)	0.99 (106)	0.69 (80)	0.98 (80)

Note: Standard errors are in parentheses. See the notes to Table 2.

Regression 3.1 of Table 3 presents the results of estimating equation (2) without the lagged dependent variable. We find that a regional dummy for African countries has significant negative intercepts, implying that Africa is the continent with the least education, by about 2.3 years per person, even after controlling for its low GDP per capita. However, the other regional dummies are not statistically significant. Past educational inequality also does not help to explain the level of education.

Regarding income, the log of income per capita and its square turn out to be statistically significant. The estimated coefficients show an inverted-U-type nonlinear relationship between income and educational attainment, implying that educational attainment decreases when the log of income per capita is over 10.4. In the sample range, however, educational attainment always increases with income, although at a declining rate. The coefficients imply that, at the mean value of log income per capita (8.1), the net marginal impact of log income per capita on educational attainment is 0.84 ($3.83–2*0.184*8.1$). Hence, a country that is twice as wealthy as another one will have about 0.6 year ($0.84*\ln(2)$) more schooling per person than the less wealthy country.

The results of Regression 3.2, which includes past levels of educational attainment, show that educational attainment is highly persistent, and in this regression the coefficient on past educational inequality turns out to be strongly positive. Greater educational inequality tends to promote educational attainment

by the population. This relationship may be consistent with the theoretical presumption that a higher dispersion of education, given its level, results in high returns to education, and hence generates stronger incentives to invest in 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 educational level is insignificant in Regression 3.4, where the 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 than with variations over time.

3.2. *Evolution of Educational 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[21]:

$$(3) \qquad \sigma^E_{j,t} = b_{0,t} + b_1 \sigma^E_{j,t-1} + b_2 E_{j,t-1} + b_3 E^2_{j,t-1} + b_3 \log y_{j,t-1} + b_D D_j + v_{j,t}.$$

The specification incorporates a nonlinear relationship between educational attainment and educational inequality. 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 educational 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 postsecondary school, so that the dispersion of education is likely to decline.[22]

[21]The square terms of educational inequality and per capita income are not included because they turn out to be statistically insignificant.

[22]To illustrate the nonlinear relationship between the level and the distribution of education more formally, consider that each person can have an educational 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 this 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 $(n_2 - n_1)/120.5$. Clearly, regardless of whether n_1 or n_2 increases, 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? 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 educational inequality declines.

Accordingly, the impact of an expansion of education on its dispersion must depend on its initial level. In equation (3), the impact of a marginal increase in E_{t-1} on σ^E is $b_1 + 2b_2E_{t-1}$, 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 this presumption is presented in Figure 4, where panels (A) and (B) plot the dispersion of education against average educational attainment for the two extreme periods in our panel data. It is clear from the figure that, at low

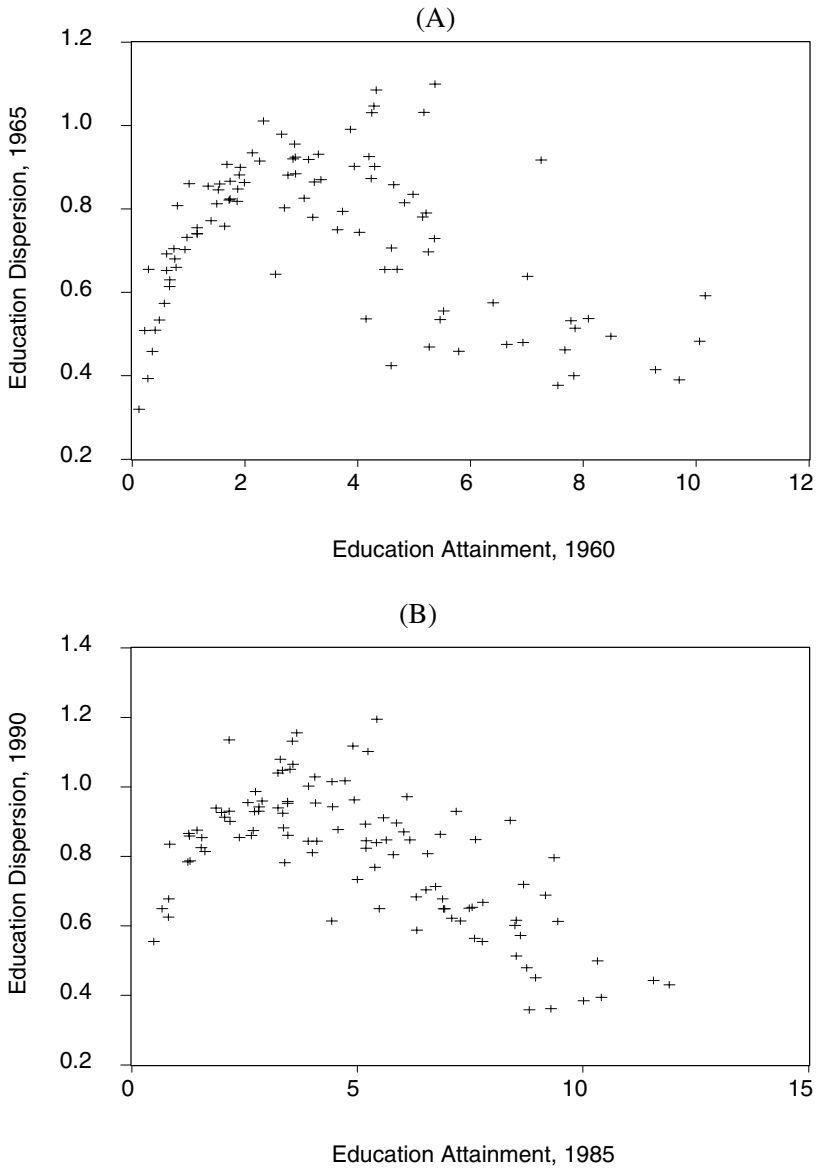

Figure 4. Education Inequality and Education Attainment

levels of education, its expansion causes an increase in dispersion, whereas for higher levels the relationship is reversed. The figures show that this reversal occurs between 3 and 5 years of schooling.[23]

TABLE 4

Regressions for Schooling Inequality

	Education Inequality			
Dependent Variable	4.1	4.2	4.3	4.4
Educational inequality (σ^E)($t-1$)		0.898		0.883
		(0.014)		(0.020)
Educational attainment (E)($t-1$)	0.066	–0.025	0.061	–0.024
	(0.010)	(0.004)	(0.011)	(0.004)
Square of educational attainment (E^2)	–0.008	0.0011	–0.007	0.0010
($t-1$)	(0.001)	(0.0003)	(0.001)	(0.0003)
Log of GDP per capita ($t-1$)	0.014	0.006	–0.018	0.007
	(0.013)	(0.004)	(0.016)	(0.005)
Social expenditure/GDP ($t-1$)			–0.011	–0.0009
			(0.002)	(0.0006)
Regional dummies				
Africa	0.066	–0.031	–0.066	–0.028
	(0.032)	(0.008)	(0.033)	(0.008)
Asia	0.130	–0.017	–0.019	–0.021
	(0.038)	(0.008)	(0.036)	(0.008)
Latin America	0.029	–0.019	–0.060	–0.023
	(0.032)	(0.006)	(0.028)	(0.007)
R^2 (number of obs.)	0.34 (92)	0.95 (92)	0.40 (65)	0.96 (65)
	0.31 (93)	0.89 (93)	0.39 (66)	0.88 (66)
	0.38 (98)	0.94 (98)	0.52 (68)	0.94 (68)
	0.39 (103)	0.90 (103)	0.46 (90)	0.89 (90)
	0.46 (105)	0.96 (105)	0.57 (94)	0.96 (94)
	0.48 (106)	0.96 (106)	0.61 (80)	0.96 (80)

Note: Standard errors are in parentheses. See the notes to Table 2.

The regression results for equation (3) are presented in Table 4. Regression 4.1 confirms the nonlinear relationship between educational attainment and educational inequality. The estimated coefficients on educational attainment and its square are consistent with the evidence of Figure 4. According to the coefficient estimates, the point at which education begins to reduce dispersion is 4.2 years.[24] The regression result also shows that initial GDP appears to have a positive relationship with educational inequality, but the coefficient on income per capita becomes insignificantly different from zero.

Regression 4.2 uses the same specification but adds a lagged dependent variable. The result shows that the dispersion of education is highly persistent over time. In this case the coefficients on educational attainment and its dispersion change sign, but this has no important implications 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 sign across specifications. Their inclusion does not affect the main results but does increase the R^2.

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

[24]In a previous version we used a different specification for nonlinearity, including an interaction term between E and its lagged value, and the results showed a cutoff at about 3.5 years.

Regressions 4.3 and 4.4 include government social expenditure as an explanatory variable. The coefficient on social expenditure is negative, implying that higher social expenditure helps to decrease the inequality of schooling. However, the estimated coefficient is statistically insignificant in Regression 4.4, which includes in addition the inequality of past schooling. In summary, we find that government social expenditure helps to explain cross-country differences in income inequality, level of educational attainment, and dispersion of education.

4. Sources of Income Inequality

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 inequality. We use the empirical result of Regression 2.4 to determine the relative contribution of each of the explanatory variables to income inequality in 1990 for 49 countries for which all necessary data are available.[25] Table A.2 in the Appendix presents the detailed results in a framework of "sources of income inequality" to show how the explanatory variables account for each country's income inequality relative to the mean value for all the sample countries. Thus this exercise looks at cross-sectional differences in inequality of income. The 10 most equal countries in the upper quintile of the income distribution include five OECD countries (Spain, Finland, Belgium, Canada, and the Netherlands), four Asian countries (Bangladesh, Sri Lanka, Taiwan, and Pakistan), and one African/Middle Eastern country (Egypt). The ten most unequal countries include five African countries (Zimbabwe, Guinea-Bissau, Kenya, Mali, and South Africa) and five Latin American countries (Chile, Panama, Brazil, Mexico, and Guatemala). Thus income inequality differs systematically across regions, and this is why regional dummies appear very significantly 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 educational factors (including educational attainment and educational 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 five most unequal African countries, the mean Gini coefficient was 0.158 higher than the world average; educational factors accounted for 0.020 of this gap, while income and social expenditure explained 0.006 and 0.008, respectively. Thus educational factors, government social expenditure, and income cannot explain the bulk of the inequality in the most unequal countries. As income level has a nonlinear relationship with income inequality, the lower income in the African countries does not contribute much to income inequality, compared with countries in other developing regions.

[25]This exercise adopts a form of "growth accounting," which is often used in the literature of cross-country growth regressions (see Barro and Lee, 1994, for example). The predicted value of the dependent variable from the regression can be broken down into the contributions of each of the explanatory variables. The contribution of each explanatory variable is calculated by multiplying the mean value of the variable by its estimated coefficient from the regression.

TABLE 5

EXPLAINING CROSS-COUNTRY DIFFERENCES IN INCOME INEQUALITY 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

Notes:

*We use the empirical result of Regression 2.4 to determine the relative contribution of each of the explanatory variables to income inequality in 1990 for 49 countries for which all necessary data are available. The list of the countries and the same type of accounting for each individual country are shown in Table A.2 of the Appendix.

**Differences from the mean value of Gini coefficients for a sample of 49 countries in 1990.

***Other factors include data characteristics and regional dummy.

The cross-sectional accounting of national differences in income inequality 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 greater educational 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 greater income inequality by 0.003 and 0.007, respectively.

The effect of income levels on regional differences in inequality is more visible in the Latin American 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 educational factors, 0.032 to the difference in income, and 0.005 to the difference in social expenditure. In OECD countries educational 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 explains the relative equality of income distribution.

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

5. CONCLUDING REMARKS

In searching for explanations of inequality around the world, one interesting issue is why inequality differs so much across countries and between regions, and how some countries have been able to reduce it. By understanding the main determinants of income inequality, we can also find policy implications that would help to reduce inequality. This paper looks closely at one of the main

determinants of income distribution, namely, education. Policymakers usually argue that efforts in the educational field reduce income inequality.

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

However, we should emphasize that a significant proportion of the variation in income inequality across countries and over time remains unexplained. 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 those of other regions. Some studies have examined the effects of macroeconomic factors on income distribution (De Gregorio, 1995; Sarel, 1997; Bulír, 1998; Li, Squire, and Zou, 1998), but they do not take account of all the educational factors we have examined in this paper. We plan to explore the connections among income distribution, education, macroeconomic factors, and government policy in subsequent research.

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.

Appendix

TABLE A.1

Regressions for Kuznets Curve (dependent variable: Gini coefficient)

	Regression Number and Period							
Independent Variables	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
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)

Notes: Standard errors are in parentheses.
*gdp corresponds to GDP per capita.
**Coefficient is multiplied by 10^{-5}.
***Coefficient is multiplied by 10^{-10}.

TABLE A.2

SOURCES OF CROSS-COUNTRY DIFFERENCES IN INCOME DISTRIBUTION, 1990

Country	Actual Gini	Predicted Gini	Explained by			
			Education	Income	Social Expenditure	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.	–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 Republic	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-Bissau	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

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

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