Inequality and The Distribution of Human Capital

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Abstract

Income distributions vary widely across countries for reasons that are not entirely well understood. Most cross-country empirical studies of inequality have proceeded with little attention to methodology, reporting reduced form correlations in Gini coefficient regressions with little effort to identify structural relationships. This paper develops an empirical accounting specification for Gini coefficient regressions analagous to a variance decomposition formula. This accounting helps to relate the Gini (which measures the size distribution of income) with the distribution of human capital endowments and factor shares by educational level. Analyzing factor distribution and factor prices separately allows a better understanding of underlying distributional changes and more appropriate tests of economic theory than previous approaches have allowed. The availability of private credit is shown to be an important determinant of equality of educational opportunity, but land inequality is not. The effect of "globalization" on factor prices is tested directly using estimates of the latent returns to education.

The professional classes especially, while generally eager to save some capital *for* their children, are even more on the alert for opportunities to invest *in* them. But in the lower ranks of society... the slender means and education of the parents... prevent them from investing capital in the education and training of their children with the same free and bold enterprise with which capital is applied to the improving of machinery of any well-managed factory.... They go to the grave carrying with them underdeveloped abilities and faculties....

–Alfred Marshall

The notion that equalizing skills will equalize incomes rests on a confusion—a confusion between equity in access to lottery tickets and equity in the value of the prizes. It is one thing for a program to... support new chances for individuals to compete on the educational and career ladders. It is something different to promise that the ladder itself will become shorter and wider as a result.... They are promising an adjustment of the structure of economic outcomes to the distribution of human skills.

–James K. Galbraith

1 Introduction

Over the past two decades, understanding the determinants of income inequality has received less attention from macroeconomists than understanding the determinants of income growth. It is not clear why. The range of (per-capita) incomes between the richest and poorest countries, an important motivation for growth research, is far less than the range of (individual) incomes *within* many countries. In some countries, for example, the average income of the richest one-fifth of the population has reached 30 times that of the poorest fifth, while in the international distribution of per-capita incomes (in PPP terms) this same ratio has only recently begun to exceed 10:1.[1] Moreover, as the table in Figure 1 (page 3) reveals, levels of income inequality vary greatly across countries, from particularly high levels in Africa and Latin America to fairly low levels in countries in Eastern and parts of Western Europe. Although inequality has risen quickly in the past decade in the transition economies, aggregate inequality is remarkably persistent over time. Even with slight increases or decreases in inequality, high (low) inequality regions tend to sustain high (low) levels of inequality. In general, the range of inequality in the time series of a single country averages an order of magnitude less than that of a cross-section at a given point in time.[2]

These empirical phenomena deserve some explanation. This paper studies the cross-country pattern of income inequality by adopting three ideas that have been central to the empirical growth literature. First, analogous to the growth accounting formula developed by Solow [32], a system of "inequality accounting" is developed based on the distribution (rather than the accumulation) of productive factors. Second, this formula is applied to cross-country data to search for inequality determinants in much the way Barro [3] and others have applied the Solow model to growth regressions. Finally, based on broad evidence that human capital is a key determinant explaining income levels of both individuals (Mincer [29], Becker [6]) and nations (e.g., Mankiw, Romer and Weil [28]), this paper focuses on the role of the human capital distribution in understanding income distributions. In doing so, it makes use of the rich cross-country dataset on the distribution of human capital constructed by Barro and Lee [5], which has been instrumental in growth regressions but has yet to be exploited fully in understanding patterns of inequality.

[1] According to World Bank data on quintile economic shares [13], several African and Latin American countries (including Brazil, Gabon, Guinea-Bissau, Guatemala, Honduras, Panama and South Africa) have had such 80/20 income ratios in the neighborhood of 30:1 (based on gross household income or adjusted comparably). The between-country ratios were calculated based on PPP estimates of per-capita income from the Penn World Tables 5.6. In 1960 the 20th and 80th percentiles of global per-capita incomes were \$640 and \$3,369, respectively; in 1990 they were \$995 and \$9,274.

[2] Comparisons using the Gini coefficient, a measure of inequality bounded between 0 (complete equality) and 100 (singularly concentrated ownership), vary across countries in a range of 20 to 60. By comparison, the Gini coefficients reported for the United States during the well-documented rise in income inequality of the 1980s and early 1990s moved from roughly 36 to 39. In the sample of countries used in this paper, the between-country variance of Gini coefficients is close to 100, the within-country variance is close to 10. For further discussion, see Li, Squire and Zou [27]

1.1 The normative importance of inequality

The assertion that income inequality should be of concern to economists is not without critics. Many factors contributing to measured inequality – such as work preferences, compensating differentials and the age-earnings profile – have no particular normative significance. Some have argued that normative statements about inequality entail inter-personal utility comparisons, making it an inappropriate object of attention for economists.[3] However, such critiques are relevant mostly to countries with equitable access to individual investment opportunities. From the standpoint of both income inequality and mobility a crucial aspect of investment is education, since – unlike physical assets, which can be transmitted through bequests – human capital must be acquired through individual investments. Human capital is a primary determinant of earnings, which composes the majority of household income flows (and thus measured income inequality). In countries where capital markets function imperfectly, the educational investment choices may be linked to the distribution of wealth, generating persistent inequality in the distribution of human capital endowments and resulting incomes. In short, the implications for social welfare are much more apparent when income inequality can be linked to individuals' human capital, because the latter is a good indicator of the degree of inequality of opportunity in a society.

Given this, the facts are startling. As of 2000, according to the Barro and Lee human capital stock data, one-quarter of the (measured) world's population has received no formal education, while nearly one-half has received no more than primary education. This suggests a substantial inefficiency may exist where large segments of the population have been unable to maximize the potential of their individual productive talents. Indeed, there is a clear correlation between educational inequality and per-capita income (see Figure 1). It is this aspect of inequality on which this paper concentrates, exploring the role of poverty and credit constraints on investment choices and market outcomes. The role of preferences, innate differences in ability, and luck are excluded in the theoretical framework that guides the empirical techniques developed in the paper.

The exact relationship between educational investments and market outcomes is still the subject of much speculation, however, as the quotes at the start of the paper suggest. One point of view is expressed by Marshall, that the nature of human capital prevents third parties from engaging in arbitrage (as they could with physical capital), allowing differences to persist in the marginal return to education across individuals. The implication is that this can generate a vicious cycle of educational underinvestment and poverty among families with initially low levels of wealth.[4] The idea that there is an underutilization of human resources

[3] Martin Feldstein, who is among those arguing normative analysis should stop at the Pareto principle, has labeled those concerned with relative inequality as "spiteful egalitarians" ("Reducing poverty, not inequality" in *Public Interest*; Fall 1999). A different view is taken by Amartya Sen (*On Economic Inequality* (Expanded Edition) Oxford: Clarendon Press, 1997), who suggests that inter-personal utility comparisons are not only possible, they occur regularly in daily life.

[4] In fact, this argument requires several implicit assumptions, which are highlighted in a formalization of the

REGION	1960	1965	1970	1975	1980	1985	1990	1995	1995/1960
Africa (Sub-Sahara)									
income gini	48.2	--	50.0	50.5	44.2	48.2	51.7	51.0	6%
education gini	80.2	--	78.8	64.8	63.9	60.9	67.2	65.5	-18%
gdp/capita	978	--	1,328	1,724	1,455	1,586	1,218	832	-15%
observations	7	0	6	7	8	11	19	14	72
East Asia-Pacific									
income gini	38.9	38.6	38.4	38.5	38.0	39.2	40.1	41.8	7%
education gini	58.9	55.0	48.4	46.0	42.8	40.2	39.1	40.2	-32%
gdp/capita	1,250	1,876	3,229	4,444	5,864	6,395	7,441	7,898	532%
observations	5	7	11	13	11	12	14	8	81
Eastern Europe & Central Asia									
income gini	28.4	25.2	29.3	27.8	24.4	26.3	26.4	34.7	22%
education gini	30.5	38.1	42.2	41.8	29.1	35.3	29.4	32.9	8%
gdp/capita	1,725	2,511	2,780	4,055	4,680	4,823	4,440	3,586	108%
observations	4	4	6	8	18	19	25	21	105
Latin America & Caribbean									
income gini	47.3	56.5	50.5	48.0	48.2	49.1	49.3	51.6	9%
education gini	43.2	62.8	49.6	46.7	44.0	48.8	44.2	43.5	1%
gdp/capita	2,684	2,302	3,874	4,357	5,580	4,005	3,726	3,565	33%
observations	11	3	18	11	14	12	19	11	99
Middle East & N. Africa									
income gini	54.1	47.9	51.2	44.4	41.1	43.4	41.6	39.8	-26%
education gini	98.4	92.7	90.6	67.4	54.2	63.5	57.3	63.6	-35%
gdp/capita	2,118	1,160	4,796	3,214	4,938	4,126	4,527	2,554	21%
observations	3	3	1	4	5	5	9	1	31
North America									
income gini	33.0	33.1	33.2	33.0	33.3	35.0	32.7	--	-1% *
education gini	28.1	27.0	24.2	24.8	18.3	18.9	20.1	--	-28% *
gdp/capita	8,577	10,157	11,544	12,985	14,714	16,080	17,614	--	105% *
observations	2	2	2	2	2	2	2	0	14
South Asia									
income gini	40.1	39.0	34.6	39.8	38.2	37.5	32.2	37.7	-6%
education gini	86.5	78.5	77.4	79.8	72.1	75.1	76.5	76.7	-11%
gdp/capita	859	989	1,089	932	1,178	1,302	1,349	1,335	55%
observations	2	4	4	4	4	5	3	2	28
Western Europe									
income gini	39.0	35.4	34.0	34.8	32.9	31.4	30.8	31.0	-21%
education gini	24.1	29.8	28.5	30.8	30.1	30.5	27.9	28.6	18%
gdp/capita	6,181	7,163	8,487	9,341	10,910	11,524	13,618	14,367	132%
observations	5	9	9	13	15	14	11	9	85
WORLD AVERAGE (wtd. by countries in region)									
income gini	42.8	38.3	41.6	39.7	36.4	37.5	39.4	41.5	-8% *
education gini	53.8	51.3	50.1	47.4	41.2	44.6	44.0	43.7	-18% *
gdp/capita	2,709	3,822	4,185	5,068	5,987	5,681	5,284	4,907	95% *
observations	39	32	57	62	77	80	102	66	515

* - change from 1960 to 1990

Figure 1:

implies an aggregate inefficiency underlying inequality, so that the goals of equity and efficiency are not only compatible, they are synonymous. In the context of later discussion offered in this paper, this line of argument assumes that the principle component of aggregate income inequality is that *between* educational groups.

In contrast to Marshall, James Galbraith's view of educational equity is more guarded. He suggests that changing the distribution of education may do little to affect the overall distribution of economic outcomes. As a result, nominal increases in education may not translate into increases in either real output or income. (One could suppose, for example, that society's demand for janitors and the wage the job commands are relatively invariant to whether the person holding the position has a high school or a college degree). Thus, although the alleviation of credit constraints may narrow differences in education levels, it might have little impact on aggregate *income* inequality. In the context of this paper, Galbraith's inequality would largely appear composed of that existing *within* educational groups.

To explore these arguments, this paper examines the role of educational inequality as a determinant of income inequality in two parts. First, it examines the Marshallian argument by studying the determinants of the distribution of human capital in a country. Secondly, it examines the impact of these distributions on aggregate inequality by decomposing the Gini coefficient into a series of *price* and *endowment* terms by educational level, examining the contribution of each. Determinants affecting factor prices, such as international trade, the level of development, and/or the average level of education in the workforce are examined in one of two ways. The first is to introduce potential explanatory variables for the latent wage coefficients in a hierarchical econometric framework. The second is to use Lorenz curve data in combination with the distribution of the human capital stock to estimate human capital returns.

The paper finds that size of the credit market does appear to decrease educational inequality (as measured by the Gini coefficient), as does increased government spending on education. The role of the latter, however, appears entirely to be in reducing the share of the population with no education whatsoever, while the role of private credit is largely in reducing inequality in attainment between levels of primary, secondary, and higher education. This lends credence to the idea that some inequality is attributable to household credit constraints. These factors also appear to lower educational premiums, consistent with a general equilibrium response to shifts in the distribution of skill in labor supply. Across countries, there is a clear, strong

argument presented in Section 2. The first is the presence of credit market constraints that prevent individuals borrowing on capital markets to achieve efficient human capital investment on their own. (Marshall's actual argument emphasizes behavior and differences in discounting rather than borrowing constraints – which could be modeled as the presence of informational constraints, but this is a trickier argument to establish and test formally). Second, as Galor and Zeira [21] have shown, for this inequality to persist as a steady-state requires a non-convexity in the human capital investment technology. (This seems a reasonable assumption, however, as fixed costs are arguably a fundamental characteristic of the education process in the real world, where each level of schooling requires several years to complete). Finally, the argument assumes that wages reflect individual productivity which can be increased through education.

correlation between inequality in the distribution of human capital among the educated and income inequality, supporting the Marshallian position. However, the evidence in Figure 1 suggests that decreases over time in educational inequality within countries have not brought about commensurate reductions in income inequality, in line with Galbraith's argument.

The paper proceeds as follows. The remainder of the introduction surveys the existing literature, contrasting the difference in methodology between single-country microeconomic and cross-country macroeconomic studies, which this paper attempts to reconcile. Section 2 discusses the relationship between the Gini coefficients of income, education, and assets. The section concludes with a discussion of the specification issues arising from attempts to quantify "human capital" by years of schooling. Section 3 examines the determinants of the education Gini, focusing on the role of credit market imperfections. Section 4 discusses approaches to identifying the returns to education in wages from aggregate inequality data and marginal distribution of education in the population. The role of international trade on these latent wage terms is explored via a hierarchical linear model. Section 5 uses decomposition techniques developed earlier to explore changes in the structure of inequality over time in various countries. Section 6 concludes.

1.2 Inequality in the Literature

The vast majority of empirical studies investigating determinants of income inequality employ data on individual wages or household incomes within a single country, such as the Panel Study on Income Dynamics (PSID) in the U.S. Using the joint distribution of incomes (henceforth denoted by y) with associated individual characteristics (a vector x) it is possible to uncover conditional income distributions $p(y|x)$, and to analyze the aggregate variance of incomes through the standard variance decomposition formula

$$Var(y) = Var_x(E(y|x)) + E_x(Var(y|x)) \tag{1}$$

The first term on the right hand side represents the component of inequality attributable to variance in the population characteristics (often referred to as "between-group" inequality) while the second term represents inequality "within-groups." Since the latter term represents the average variance not otherwise attributed to observed characteristics, it also possible with such a methodology to address the question of "how much" inequality can be explained (e.g., Cowell and Jenkins [11]).

In the few countries where microeconomic data is available, this approach has proved to be very useful in understanding sources of inequality and in exposing trends underlying shifts in the income distribution. The question this paper seeks to answer is slightly different – why inequality differs in levels so widely across countries – and a very different approach has been taken in the macroeconomic literature addressing the question.[5] The methodology employed

[5] The difference in approaches, and the reason for each, can be highlighted with an analogy to the empirical

in cross-country studies is largely data-driven, reflecting the clear trade-off that exists between the scope of countries one can include in a study and the detail and quality of the data available for each country.

Following efforts by researchers at the World Bank and elsewhere to compile cross-country panel datasets of Gini coefficients from household studies taken over the past half-century, a number of papers have emerged using this data to understand the macroeconomic role of inequality. For the most part, however, these papers (e.g., Alesina and Rodrik [1], Bénabou [7], Forbes [20], Barro [4], and Bannerjee and Duflo [2]) have focused on the role of inequality as a determinant of investment and growth, and not as an object of interest in itself.

The lack of attempts to offer an "explanation" for levels of income inequality across countries may reflect the inherent difficulty of doing so, given the breadth and complexity of the forces at work and the necessary sacrifice of rigor. Economic models of income inequality in the literature often differ in the measures and concepts of income inequality they use, making it difficult to nest all the empirically relevant mechanisms in a single holistic model of inequality.[6] As a result, perhaps, what empirical work there is studying inequality at the cross-country level has taken a relatively *ad hoc* approach, estimating reduced form regressions such as

$$Inequality\ Index_j = \sum_{k=1}^{p} \boldsymbol{\beta}_k X_{kj} + \varepsilon_j \tag{2}$$

for each country j, using p potentially significant covariates.

Li, Squire and Zou [27], Gustaffson and Bjorklund [24], and Barro [4] are recent examples of such work. The first two papers present such regressions as "tests" of various predictions offered by economic theory. Li, Squire and Zou focus on two in particular – the role of credit constraints, and the role of political economy (essentially a story of institutional strength, representing protections from the will of the rich afforded to the poor). They find evidence for both effects, testing credit constraints with variables such as the ratio of private credit to GDP and a Gini coefficient for land use (proxying asset inequality), and testing the political economy with a measure of civil liberties and the initial level of secondary schooling. Gustaffson and Bjorklund employ a wide range of variables such as import shares, unionization and unemployment rates, industrial sectoral shares and demographic variables such as population growth. Barro's focus appears to be on prediction rather than explanation, establishing the reduced form correlation of the Gini coefficient with levels of education, dummies for Africa and Latin America, per-capita income (finding the standard Kuznets curve), and – most

growth literature: cross-country regressions arguably have contributed to our understanding of the process of economic growth in ways that data from a panel of U.S. firms alone could not.

[6] For instance, labor economics focuses on the role of individual abilities and investment decisions in individual wage earnings, while public economics usually considers how tax and transfer policies affect a broader measure of household income. The international trade literature studies relative factor price movements holding factor supplies constant, while the macro literature usually considers the distribution and dynamics of the factor supplies.

intriguingly – a positive correlation with a measure of "openness," decreasing in per-capita income. In effect, this latter finding goes against the conventional wisdom of the Stolper-Samuelson theorem, that trade will raise inequality in (skill-rich) developed countries and lower inequality in (skill-poor) developing countries.

The trouble with making such arguments is that reduced form relationships with summary inequality statistics can be difficult to evaluate.[7] In particular, inequality measures like the Gini coefficient are often related to the second moment of the distribution and may have non-linear relationships with variables that are linearly correlated with the first moment (such as the use of average years of schooling in Barro [4] and Li, Squire and Zou [27]), a problem discussed in the Appendix. Additionally, it is by no means certain that variables used in these reduced form regressions have their impact through the structural mechanisms to which they are attributed. For instance, it should not be surprising that asset inequality (the land Gini coefficient) is correlated with income inequality, as there is a trivial structural relationship through the distribution of land rents. To test more accurately the impact of credit constraints, requires that we explore the role of asset inequality on *investment* decisions rather than outcomes. In short, the challenge seems to be to establish closer links with economic theory, making the best use of the data available.

2 Inequality Accounting

Intuitively, the idea underlying the accounting exercises in this paper is that variance in incomes reflects two components: the conditional distribution of incomes on education, and the variance of education across individuals. If we hypothesize, for example, that incomes in country j are a function of individual i's human capital, $y_{ij} = w_j(h_{ij})$, then to a first-order approximation of the wage function, it can be shown that

$$I_j(y) = \varepsilon_j^w * I_j(h) \tag{3}$$

where the coefficient of variation $I(x) = \frac{\sqrt{Var(x)}}{E(x)}$ indexes inequality of variable x, and $\varepsilon^w \equiv \frac{dw/\bar{w}}{dh/\bar{h}}$ represents the elasticity of individual wages with respect to human capital. At minimum, these two distinct dimensions – the endowment effect ($I(h)$) and price effect (ε^w) – should be distinguished in an explanation of inequality, as it are these quantities, and not aggregate income inequality $I(y)$,on which economic theory generally offers predictions. For example, models of credit constraints discuss investment choices affecting $I(h)$, while international trade theory offers predictions on relative factor prices such as the ratio of skilled to unskilled wages (embodied in ε^w).

Making this distinction also highlights the problems with the reduced form regression

[7] The same inequality statistic can be generated by different income distributions, for example. In addition, movements in the income distribution may not affect different inequality statistics in the same way.

specification of equation (2), as theory does not always offer an unambiguous reduced form relationship between the Gini coefficient and covariates affecting either relative endowments or prices. A shift in skill-biased technological change that raises ε_w, for instance, might raise, lower, or leave $I(y)$ constant, depending on the elasticity of educational investment choices to the incentives embodied in the rising skill premium and the initial distribution of skill. Similarly, a reduction in credit constraints that increased average levels of educational attainment might lower or raise aggregate inequality, depending on the initial distribution of education.[8]

With reference to Figure 1, it is interesting to note that in every region of the world except Western Europe the Gini coefficient for years of schooling has fallen much faster – or risen less – than income inequality. This may suggest that the return to years of schooling is rising, or it may be that the contribution to inequality of factors other than education has grown. Rising skill premiums are consistent with the experience of a few countries like the U.S., however many of the explanations suggested for rising skill premiums in the industrialized world cannot immediately be attributed to inequality in the developing world.[9]

The task undertaken in this paper is to attempt identification of the conditional relationship of incomes and education, using data not on the joint distribution of individual incomes and education as in the microeconomic literature, but using macroeconomic data on the marginal distributions of income and education. This approach is sometimes described as an "ecological inference problem." Clearly to attempt such identification requires some assumptions about the joint (or conditional) distribution, and any subsequent results must be interpreted with the validity of those assumptions in mind. The principal assumption maintained throughout this paper is that incomes are increasing in the level of education. While intuitively reasonable, this is a strong condition: it implies, for instance, that a person with secondary (or less) education earning more than someone with college education occurs with zero probability. This effectively allows us to reinterpret Lorenz curve data (including the Gini coefficient statistic) as income shares not over quantiles of the population but over rates of education. (Figure 10 in the Appendix may help to clarify this point).

[8] Intuitively, if the share of the population that is "skilled" were 10%, an increase in that share would tend to increase most inequality measures, while if the initial skilled share were 90%, those measures would tend to decrease. This is discussed briefly in Appendix B.

[9] The Stolper-Samuelson Theorem discussed earlier is one example. Additionally, arguments that the skill-bias of labor demand has outpaced growth in the skilled labor supply are more questionable for the developing world. It is likely that the "frontier" technologies invented in the U.S. and elsewhere are more skill-biased than those being transferred to the developing world, which have usually had time to become standardized for production processes employing lesser-skilled workers. Moreover, growth in average educational levels among the workforce has been much more rapid in the developing world.

2.1 The Gini Coefficient

This section of the paper outlines the general methodology for decomposing the Gini coefficient, the most widely available measure of inequality.[10] Although the Gini coefficient has a number of desirable properties from a methodological standpoint as a measure of inequality, it is somewhat difficult to manipulate mathematically.[11] The Gini coefficient can be written (e.g., Sen [31])

$$G(y) = \frac{2}{n^2\bar{y}} \sum_{i=1}^{n} \left(i - \frac{n+1}{2} \right) y_i$$

where i represents the individual's income rank (from low to high), n is the size of the population, and $\bar{y}$ represents average (per-capita) income. Individual income is the sum of the returns to their productive inputs in production: wages (the return to human capital) and physical capital investment returns, or $y = w(h) + rk$. Substitution implies that $G(y)$ can be decomposed according to income source as

$$\begin{aligned} G(y) &= \frac{\bar{w}}{\bar{y}} \left[\frac{2}{n^2\bar{w}} \sum_{i=1}^{n} \left(i - \frac{n+1}{2} \right) w(h_i) \right] + \frac{r\bar{k}}{\bar{y}} \left[\frac{2}{n^2\bar{k}} \sum_{i=1}^{n} \left(i - \frac{n+1}{2} \right) k_i \right] \\ &= (1-\theta)\tilde{G}(w) + \theta\tilde{G}(k) \end{aligned} \tag{4}$$

where θ represents capital's share of national income $\left(\frac{rK}{Y}\right)$, and $\bar{w} \equiv \frac{1}{n}\sum w(h_i) = (1-\theta)\bar{y}$ are average earnings in the economy.

The notation $\tilde{G}(\cdot)$ is used to emphasize that $\tilde{G}(w)$ and $\tilde{G}(k)$ are not necessarily true Gini coefficients since they are constructed based on the ranking of *total* income and not wage and capital incomes, respectively. Any function $\tilde{G}(x)$ constructed using a ranking other than its own employs a non-monotonic weighting of x, so it must be the case that $\tilde{G}(x) \leq G(x)$. However, if either $w(h_i)$ or k_i are non-decreasing in the income rank i, then $\tilde{G}(\cdot) = G(\cdot)$ and there is no measurement error. In the theoretical model underlying this paper (briefly summarized in the Appendix), higher income always reflects both higher education and a higher wage, however this is not true for asset income.[12] Therefore, we will proceed by

[10] It is well-known that the Gini coefficient is notgenerally decomposable by income source or population group, because the weighting of the distance of values from the mean depends on the rank ordering of the value in the population. (The weighting used in the variance, by constrast, is anonymous: the distance $(x-\mu)$ is weighted by itself). It is possible, however, to offer a decomposition if the factors are hierarchical (e.g. with unskilled and skilled labor), so that the ranking of the factor incomes within groups and between groups is preserved.

[11] The Gini is scale independent in both income and population and it satisfies the Pigou-Dalton transfer condition, making it a justifiable measure of what we commonly conceive as "inequality" (see Sen [31] for discussion). However, unlike the Theil coefficient or coefficient of variation, it is not freely decomposeable by population group or income source. The decomposition exercises in this paper are done at the cost of some restrictive assumptions, principally those in equation (5).

[12] Intuitively, educational investments are made only when they increase resulting incomes. They do so by increasing wages. So the rank ordering of education, wages and incomes will be the same.

assuming the following relationships hold:

$$\begin{aligned} \tilde{G}(h) &= G(h) \\ \tilde{G}(w) &= G(w) \\ \eta &\equiv G(k) - \tilde{G}(k) \geq 0 \end{aligned} \tag{5}$$

where η represents a non-negative measurement error.

Equation (4) captures the basic accounting relationship between inequality of income and that of factor endowments, but the direct relationship between inequality of income and human capital is not yet explicit, as it depends on both the unknown function $w(h)$ and the ability to measure h appropriately. A standard approaches to the latter problem has been to proxy h by "years of schooling." If we use a local linear approximation of the wage function around mean years of schooling (as in equation 3) then, together with the assumptions in (5), equation (4) becomes

$$G(y) = (1-\theta)\,\varepsilon^{w} G(h) + \theta G(k) + \theta\eta \tag{6}$$

In other words, the factors that determine income inequality do so through the distribution of productive factors and the relative factor prices, captured in the factor shares θ and $(1-\theta)$ and the wage elasticity ε^{w}.[13] Given data on the Gini coefficients for years of schooling and asset inequality equation (6) can be estimated by OLS across a sample of countries to estimate the relative contributions of inequality in the distribution of factor endowments.

2.2 An Accounting Formula for the Gini Coefficient

In several instances, it will be convenient to present the Gini coefficient as a sum of terms representing the "inequality" contributed by certain subsets of the population. Consider, for example, the situation in which individuals ranked according to their income $i = 1, ..., n$ can be allocated into one of $M + 1 \leq n$ distinct sets $m = 0, 1, ..., M$ with the property that

$$y_i \geq y_j \text{ if and only if } i \in m \text{ and } j \in m' \leq m \tag{A1}$$

The specific example used in this paper involve income ranks i, and educational levels m. In this case, assumption (A1) implies that the poorest individual with education level m has at least as large an income as the richest individual with education level $m-1$. The following proposition states that when this assumption holds, the Gini coefficient can be written as the sum of two terms representing the average inequality within each educational group, and the inequality between the group means. In effect, such a specification is very much like the variance decomposition formula in equation (1).

[13] Specifically, the coefficient on $G(h)$ would be $\frac{\bar{w}}{\mu}\frac{dw}{dh}\frac{\bar{h}}{\bar{w}}$, which is equal to labor's share of income times the elasticity of the wage function with respect to the level of human capital, as given in equation (6)

Proposition 1 *Let individuals be ranked $i = 1, ..., n$ according to the value of some variable y_i, and let these individuals each belong to a group, indexed by $m = 0, 1, ..., M$. If the ranking of m and i satisfy (A1), then the Gini coefficient for the variable y, $G(y)$, can be written as*

$$G(y) = \sum_{m=0}^{M} p_m s_m G_m(y) + \sum_{m=0}^{M} s_m \left[F_{m-1} - (1 - F_m)\right] \tag{7}$$

where p_m represents the share of the population in group m, F_{m-1} the share of the population in groups indexed below m, $(1 - F_m)$ the share in groups indexed higher than m, s_m is the share of the total value of y possessed in group m, and $G_m(y)$ represents the Gini coefficient for the distribution of y within group m.

Proof. *Recall the definition of the Gini coefficient for a variable y with mean μ in an economy of n agents:*

$$G(y) = \sum_{i=1}^{n} a(i) \frac{y_i}{\mu} \quad \text{where weight } a(i) = \frac{2}{n^2}\left(i - \frac{n+1}{2}\right)$$

The index i is, by construction, ascending in the value of y. Define $a_m = \min\{i : i \in m\}$, $b_m = \max\{i : i \in m\}$, $n_m = b_m - a_m + 1$ as the number of individuals in group m, and $\bar{y}_m$ as the mean value of y in group m. Since the index m is also ascending in the level of y, the Gini formula above is equivalent to

$$\begin{aligned} G(y) &= \sum_{m=0}^{M} \frac{n_m^2}{n} \frac{\bar{y}_m}{\mu} \left(\sum_{i=a_m}^{b_m} \frac{2}{n_m^2 \bar{y}_m} \left(i - \frac{n+1}{2}\right) y_i \right) \\ &= \sum_{m=0}^{M} p_m s_m \left(\sum_{i=a_m}^{b_m} \frac{2}{n_m^2 \bar{y}_m} \left(i - a_m + 1 - \frac{n_m+1}{2}\right) \right) \\ &\quad + \sum_{m=0}^{M} p_m s_m \left(\frac{2}{n_m^2 \bar{y}_m} \left(a_m - 1 + \frac{n_m}{2} - \frac{n}{2}\right) \sum_{i=a_m}^{b_m} y_i \right) \\ &= \sum_{m=0}^{M} p_m s_m G_m(y) + \sum_{m=0}^{M} s_m \left(2\left(\frac{a_m - 1}{n}\right) + \frac{n_m}{n} - 1 \right) \end{aligned}$$

where $p_m \equiv \frac{n_m}{n}$, $s_m \equiv \frac{\bar{y}_m p_m}{\mu}$, $G_m(y) \equiv \sum_{i=a_m}^{b_m} \frac{2}{n_m^2 \bar{y}_m}\left(i - a_m + 1 - \frac{n_m+1}{2}\right)$, the Gini coefficient for the distribution of y within group m. Defining $F_{m-1} \equiv \frac{a_{m-1}}{n}$ as the share of the population in groups indexed up to and including $m-1$, and defining F_m analogously, we can rewrite the

Gini as

$$\begin{aligned} G(y) &= \sum_{m=0}^{M} p_m s_m G_m(y) + \sum_{m=0}^{M} s_m \left(2F_{m-1} + p_m - 1\right) \\ &= \sum_{m=0}^{M} p_m s_m G_m(y) + \sum_{m=0}^{M} s_m \left(F_{m-1} - (1 - F_m)\right) \end{aligned}$$

■

When the $M + 1$ groups are interpreted as factors of production of different qualities, as is the case with labor of various skill levels, this formula provides a convenient way to relate the Gini coefficient, which measures the size distribution of income, to factor income shares s_m, the subject of most economic theory.

2.3 Constructing a Gini coefficient for human capital

We can use the Gini formula above to construct values of $G(h)$, the Gini for the distribution of human capital, using years of schooling as a scalar measure of human capital. Data on the length of schooling cycles is available from UNESCO, while data on the distribution of educational attainment among individuals in the country is given in the Barro-Lee human capital stock dataset. The Gini coefficient for years of schooling is then given by the equation

$$G(h) = \sum_{m=0}^{M} \frac{h_m}{\bar{h}} p_m \left(F_{m-1} - (1 - F_m)\right)$$

where h_m is the length of the schooling cycle m, and $\bar{h}$ is the average years of schooling in the country. By construction, there is no inequality in years of schooling among individuals in the same education group. Although many individuals do not complete a full education level, the Barro-Lee data provide seven levels of attainment (no education, incomplete primary, complete primary, incomplete secondary, etc.) and it is assumed that those with an "incomplete" level of schooling received one-half of the total years of schooling at that level.[14]

However, there is a statistical peculiarity that arises when using years of schooling as a measure of human capital – the correlation between the share with "no education" and the educational Gini is over .95.[15] This relationship can be seen clearly in Figure 2. The

[14] Thomas, Wang and Fan [33] of the World Bank have also constructed educational Gini coefficients for a subset of the countries employed in this paper. They use a different formula for generating their estimates, and a different source for length of schooling cycles, but obtain very similar results. The correlation between the measures is roughly .98.

[15] This issue does not appear to have received much attention in the emerging strand of literature using educational inequality statistics at the World Bank (e.g., Thomas, Wang, and Fan [33], Thomas et. al. [34]) and elsewhere. This is unfortunate, since a number of the relationships suggested between "educational inequality" and other variables (such as per-capita income) may be confusing the role of educational inequality

reason is that the share of total years of schooling among those with "no education" is zero, and this swamps all other aspects of the educational distribution (recall, for example that a Gini coefficient of 100 occurs when all but one individual have nothing). The basis for this correlation can be shown formally using the decomposition formula (7) with two groups: those with some education ($m = 1$) and those without any education. ($m = 0$). In this case, the Gini coefficient becomes

$$\begin{aligned} G(h) &= [p_0 s_0 G_0(h) + p_1 s_1 G_1(h)] + [s_0 (0 - (1 - p_0)) + s_1 (p_0 - 0))] \\ &= p_1 G(h|h > 0) + p_0 \end{aligned} \tag{8}$$

as the "between-inequality" term simplifies to simply p_0, the share of the population with no education. Where a small fraction of the population has no education (as in developed countries), the educational Gini coefficient reflects inequality among those going to school ($G(h|h > 0)$). Where a large fraction of the population has no education, the Gini coefficient for years of schooling asymptotically attains this share.

The figure offers no indication that the same relationship holds for the income Gini coefficient, which has only a .33 correlation with p_0. This is because with $h_0 = 0$ there is in effect an infinite premium to the next higher education level, while since $w_0 > 0$, the wage premium from receiving some education is finite. Clearly, therefore, the linear relationship between the Gini coefficients of income and human capital will not be borne out in the data when using years of schooling as a proxy for human capital. As a result, the analysis that follows will typically employ both the composite educational Gini, and the "between" and "within" educational components expressed in equation (8).

3 Decomposing Inequality by Factor Components

Given data on the Gini coefficients of income, human and physical capital, it is possible to use cross-country variation to estimate the decomposition equation (6) using the regression

$$G(y) = \beta_0 + \beta_1 G(h) + \beta_2 G(k) + \varepsilon \tag{9}$$

The components $(\beta_0 + \varepsilon)$ represent the contribution of additional unobserved income sources plus the measurement error. Under the assumption of linear returns, β_1 reflects labor's share in national output $\left(\frac{wL}{Y}\right)$ times the elasticity of the wage function, and β_2 the share paid to physical assets.[16] Substituting in equation (8) for $G(h)$, we can offer additional flexibility

with that of average education levels. This point is explained in greater detail in other research (Hopkins [23]).

[16] If $w(h)$ is concave, the earnings distribution will be compressed relative to the education distribution, and the estimated coefficient β_1 will be smaller than $\left(\frac{wL}{Y}\right)$. If $w(h)$ is convex, we are likely to find a β_1 that is larger than $\left(\frac{wL}{Y}\right)$. However, the reduced form correlations between inequality of income and education are of

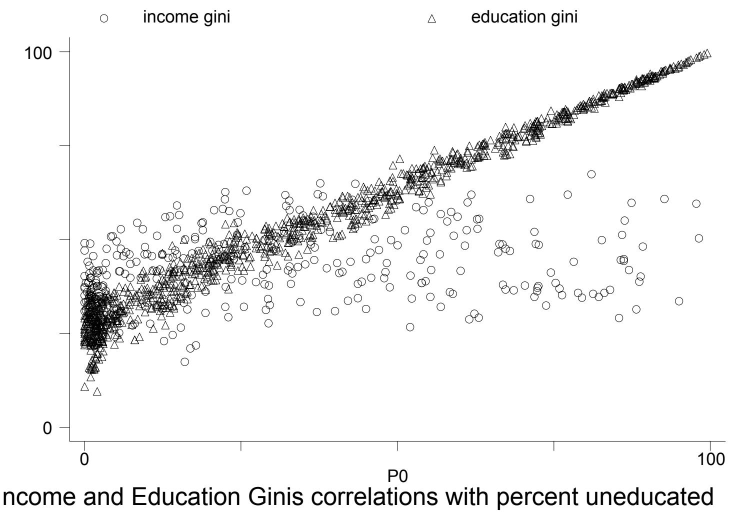

Figure 2:

by estimating the partial correlations with the between- and within- educational components separately by regressing

$$G(y) = \beta_0 + \beta_1 p_0 + \beta_2 G(h|h > 0) + \beta_3 G(k) + \varepsilon \tag{10}$$

3.1 Data

Certainly the biggest hurdle faced in cross-country inequality research is the scarcity of detailed, reliable, and comparable data for the majority of the world's countries. The most widely available inequality statistic is the income Gini coefficient, which were compiled from two sources, the Deininger-Squire (**DS**) database (described in [13]) available from the World Bank, and the World Income Inequality Database (**WIID**) [35] available through the United Nations Development Program.[17] The dataset used in this paper contains 515 income Gini coefficients, covering 137 countries from 1960-1995, at five year intervals. This is an unbalanced panel, covering 47% of a possible 1,096 observations. Although the richest countries have the most complete data, 70% of the observations are for countries classified by the World Bank as developing, a much higher share than is typical for work on income inequality. The total number observations that could be employed varied by the particular exercise, however, according to the availability of data on other variables of interest.

interest, regardless. The interpretation as factor shares is important only as a benchmark for assessing the regression specification.

[17] Only WIID observations labelled "OK" and, with a few exceptions, only DS observations included in their "high quality" set were used.

Specific details regarding construction of the dataset are available from the author; however, there are a few important points regarding the data that are worth noting here for readers unfamiliar with the source data. Cross-country comparisons of inequality are complicated by substantial variation in the methodology of the surveys used. In particular, the surveys differ according to whether they used (i) income, earnings, or expenditure data; (ii) household or personal income data, and (iii) gross or net (after-tax) income. Different approaches to correcting for these differences have been taken in the literature. For instance, Bénabou [7] uses dummy variables in his regressions to control for survey type, while Forbes [20] uses a simple fixed correction, adding 6.6 to Ginis constructed using expenditure data. In this paper generating ex-ante comparability among the observations was eased by the drawing from a more comprehensive pool than that used in earlier studies.[18] Nevertheless, differences among survey types remains a persistent problem in cross-country inequality research.

Both as a benchmark, and to improve upon so-called "standard corrections" – which can be biased if estimated in a cross-section, since survey methods are correlated with levels of inequality[19] – country-specific fixed-effects regressions were run on nearly 3,000 observations of the **WIID** database to estimate the effects of each survey type. This approach allows for a "correction" for survey type similar to that used by Forbes, but with a higher degree of accuracy by estimating the effect of surveys using only variation within each country. The resulting adjusted Gini (the variable "*adjgini*") is used in the following tables and analysis.

The process of generating Gini coefficients for human capital was described earlier. Since Gini coefficients for inequality of physical capital assets are not available across countries, I follow the lead of others, such as Deininger and Olinto [12], who use Gini coefficients constructed from land use data based on data from the FAO World Census of Agriculture as a measure of asset inequality. These estimates are only available for a cross-section of 59 countries; without variation over time, the land Gini enters as a country-specific fixed effect. A summary of the data is given in following table.

Variable	Countries	Years	Obs.	Source
Income Gini (`adjgini`)	137	1960-95	515	Deininger-Squire [13] & WIID [35]; adjusted to correct for survey type
Education Gini (`edgini`)	112	1950-2000	979	author's calculations (see text)
Asset Gini (`landgini`)	59	circa 1970	59	from Deininger and Olinto [12] based on FAO World Census

Estimates of the marginal density functions for each Gini coefficient appear in Figure 3.

[18] Whenever possible, the maximum number of observations were drawn from the same source. This generally applied to the time series within countries, but in some cases also applied to authors who conducted surveys in multiple countries.

[19] This is not a theoretical but a practical point: survey types are often correlated with particular regions. For example, surveys measuring net personal expenditure happen to be prevalent in (relatively high-inequality) African countries.

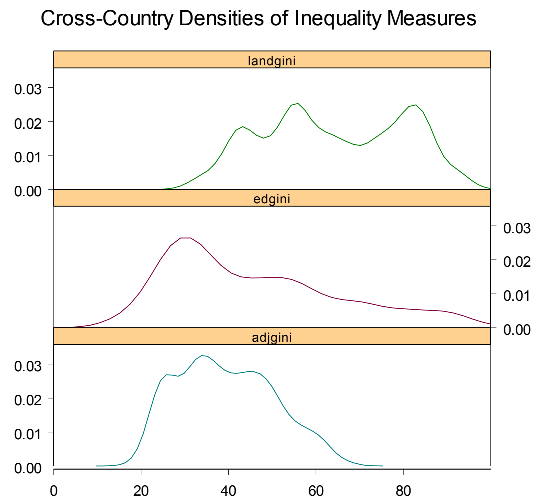

Figure 3: On average, income and human capital are more evenly distributed than land although inequality of human capital varies much more across countries than inequality of income.

The density estimates reveal a much narrower support for the income Gini than those of either education or land. Mean income inequality is approximately the same as that of educational inequality. Mean land inequality is much higher, however, confirming the conventional wisdom that physical assets are generally more concentrated than income. Although only the density of land inequality should be interpreted as representing a pure cross-section at a point in time, the density of income inequality has been relatively constant. Mass in the right tail of educational inequality has shifted in towards the mean over time, but the basic shape of the distribution in a cross-section does appear roughly as pictured in Figure 3.

3.2 Preliminary Evidence on Inequality Relationships

Figure 4 reports the results of the decomposition regressions (9) and (10) using pooled observations in the panel. As expected, decomposing the education gini to isolate the contribution of inequality among those with some schooling from the inequality between those with and without schooling reveal the former to be much more important in explaining income inequality. On the margin, a one-point increase in the Gini coefficient among those with schooling is associated with an increase in the income Gini coefficient of more than 0.5.[20]

[20] The actual effect will depend on the share with some schooling $(1 - p_0)$.

Gini coefficient decomposition regressions dep. var: adjusted income Gini coefficient				
variable	(1)	(2)	(3)	(4)
education gini	0.20	0.19		
	0.02	*0.02*		
p_0 (% no educ.)			0.26	0.26
			0.03	*0.03*
within-ed ineq			0.48	0.49
$(1-p_0)G(h\|h>0)$			*0.12*	*0.12*
land gini		0.25	0.24	
		0.03	*0.03*	
constant	32.1	16.7	9.8	24.8
	1.18	*2.17*	*3.57*	*3.14*
R^2	0.17	0.35	0.36	0.18
no. obs.	381	272	272	381

Figure 4:

Including the land Gini as a proxy for asset inequality helps to explain some additional cross-country variation in income-inequality (as the R^2 rises from roughly one-fifth to one-third), but has no affect on the estimated coefficients on the educational Gini measures.

Despite the apparently robust coefficients, these pooled regressions mask two sources of heterogeneity in the coefficient estimates, revealed in Figure 5. The first is that the correlation between income and education inequality appears only to exist in a cross-section: within countries over time the correlation is not significantly different from zero. This is not surprising given the data in Figure 1, which showed levels of income inequality remaining relatively constant in most countries over time, despite falling educational inequality. A similar issue has been raised in the literature testing the Kuznets curve hypothesis: the curve has been "found" in a cross-section at points in time, but not in the time-series of development experience of countries. It is possible that both phenomena – the Kuznets curve relationship with per-capita income and the correlation of income and educational inequality – are related to general equilibrium wage effects. Discussion of this point is beyond the scope of the current paper and thus left to future research, but the basic intuition is sketched out in Appendix B for the interested reader.

The second source of variation in coefficients comes from the fact that the relative importance of the human capital distribution relative to the land distribution varies significantly by income level. Not surprisingly, the relative contribution of land inequality to income in-

Regression of Income Gini on Education Gini using year fixed effects
(estimated using differences among countries within time periods)

Inc. Group:		lower	lower-middle	upper-middle	high (not OECD)	high (OECD)
variable						
constant		48.2	29.7	2.9	-5.3	25.4
	std. error	*28.0*	*7.8*	*12.7*	*8.5*	*3.8*
P0 (between ed ineq.)		-0.30	0.10	0.52	0.30	0.18
	std. error	*0.24*	*0.09*	*0.16*	*0.08*	*0.09*
within-ed ineq.		-1.19	0.16	0.86	1.83	0.25
	std. error	*0.82*	*0.28*	*0.43*	*0.40*	*0.11*
land gini		0.44	0.16	0.19	--	0.03
	std. error	*0.15*	*0.05*	*0.06*	*--*	*0.04*
obs		46	69	45	21	109
R^2	within-years	0.39	0.26	0.40	0.70	0.09
	between-years	0.09	0.22	0.05	0.24	0.32
	overall	0.35	0.24	0.35	0.58	0.08

Regression of Income Gini on Education Gini using country fixed effects
(estimated using differences over time within countries)

Inc. Group:		lower	lower-middle	upper-middle	high (not OECD)	high (OECD)
variable						
constant		79.1	46.6	39.5	27.7	39.1
	std. error	*30.1*	*8.2*	*5.2*	*13.1*	*2.9*
P0 (between ed ineq.)		-0.41	0.12	0.06	0.08	-0.14
	std. error	*0.33*	*0.11*	*0.07*	*0.08*	*0.12*
within-ed ineq.		-0.85	-0.15	0.17	0.38	-0.17
	std. error	*0.96*	*0.24*	*0.19*	*0.64*	*0.11*
obs		82	86	74	21	118
R^2	within-countries	0.08	0.14	0.01	0.07	0.03
	between-countries	0.09	0.07	0.36	0.96	0.16
	overall	0.12	0.06	0.48	0.56	0.05

Figure 5:

equality is greatest in the poorest countries, and falls to approximately zero in rich countries, where the distribution of land reflects occupational choice (such as farming) more than asset wealth. In contrast, the ability of the education Gini to explain patterns of income inequality appears to rise quickly with level of development, but interestingly, is lower among the OECD countries than some middle-income and higher-income East Asian countries.

Whether these coefficients should be interpreted structurally (as labor's share of income multiplied by the wage elasticity) or as an artifact of the ability of years of schooling to proxy for human capital is unclear, however. It should be recognized that a structural interpretation applies only to the distribution of human capital, not education, and that the relative contribution of unobserved sources of human capital investment is likely to be much greater in poorer countries without widespread access to formal education.

4 The Determinants of Educational Inequality

Establishing the ability of the education Gini to explain differences in income inequality across countries naturally raises questions about the determinants of educational inequality. In their evaluation of the role of capital markets imperfections on inequality, Li, Squire and Zou [27] found a negative coefficient on a broad measure of financial depth (M2/GDP) and a positive coefficient on land inequality in regressions using the income Gini. In most models of capital market imperfections, the specific channel by which credit constraint affect inequality is through the distribution of educational attainment, so it is of interest to examine whether this is in fact the case. This section of the paper presents a test of this premise using a more theoretically appropriate measure of private credit (as suggested by Levine, Loayza and Beck)[21] and government educational expenditures (from the World Bank [18], based on IMF statistics), both expressed as a percentage of GDP.[22]

Dependent variable: Gini coefficient for years of schooling								
covariate	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
ln GDP/cap	-16.86	*-0.50*	-1.66	-10.89	*-1.13*	-10.81	-1.65	*-0.55*
std err:	0.80	*0.33*	0.46	1.27	*0.63*	1.41	0.66	*0.86*
priv. Credit	*-2.74*	-3.55	-2.56	*-3.08*	-3.94	-4.55	-4.05	-5.36
std err:	2.50	0.71	0.94	*2.08*	0.99	2.24	1.03	1.15
gov't ed. exp.	-1.66	*0.01*	0.32	*-0.53*	*0.13*	*-0.12*	*0.17*	*-0.03*
std err:	0.31	*0.09*	0.12	*0.52*	*0.20*	*0.54*	*0.21*	*0.31*
% no education		0.71	0.69		0.65		0.64	0.60
std err:		0.01	0.01		0.02		0.02	0.02
land gini			*0.02*	*0.00*	*0.02*	*-0.01*	*0.02*	n/a
std err:			*0.01*	*0.10*	*0.03*	*0.10*	*0.03*	
saving						*0.08*	*0.03*	*0.01*
std err:						*0.07*	*0.03*	*0.03*
[constant term]	192.41	33.56	41.09	139.01	38.77	136.79	42.29	37.25
std err:	5.99	2.86	4.09	12.67	5.81	13.37	5.92	7.16
# obs	430	430	296	296	296	265	265	265
R^2 (adjusted)	0.68	0.97	0.96	0.63	0.96	0.66	0.96	0.96
type	pooled	pooled	pooled	Rdm Eff.	Rdm Eff.	Rdm Eff.	Rdm Eff.	Fixed Eff.
numbers in italics represent variables *not* significant at the 5% level								

Figure 6:

[21] They write, "while PRIVATE CREDIT does not directly measure the amelioration of information and transaction costs, we interpret higher levels of PRIVATE CREDIT as indicating higher levels of financial services and therefore greater financial intermediary development."

[22] In some early years of the sample where government educational expenditure breakdowns were not available, data was imputed using the total government spending that year times the ratio of government educational expenditures to total government spending in the most proximate year.

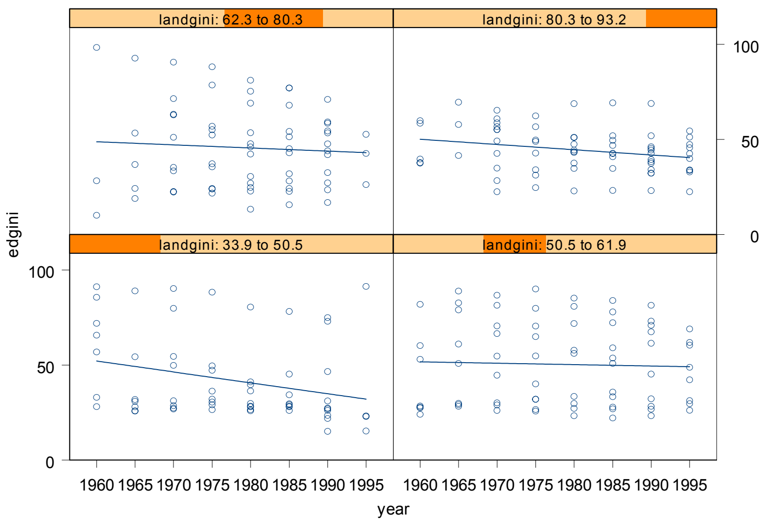

Figure 7: Poverty and persistence: educational inequality has fallen most quickly in countries with the most equal distribution of wealth.

The results presented in Figure 6 confirm that inequality in years of schooling is decreasing in the level of private credit: the partial correlation is negative, significant, and robust to the inclusion of other controls. The economic impact of an increase in private credit of 10% of GDP is between .3 and .5 of a point on the Gini coefficient (out of 100). The role of government educational spending at first appears to be greater than private credit – in column (1) it appears that an increase in spending of just 1% of GDP would lower the education Gini by 1.6. However, columns (2) through (8) reveal that the coefficient is not robust to additional controls. In accordance with theory the greatest "explanatory" power comes from the share with no education: after controlling for this effect, which is highly negatively correlated with level of development, the role of income in educational inequality is shown to be much less. Still, a doubling of GDP/capita appears to be associated with a reduction of roughly 1.6 in the education Gini.

The economic model also predicts that educational attainment and savings are substitutes, which cannot be refuted with the data. However, given the aggregate nature of the statistics and the relatively large standard errors on the estimated coefficients, the exact relationship between individual savings and education behavior is difficult to predict with certainty. Interestingly, it appears that the role of asset inequality in generating inequality of educational opportunity predicted by our model is not borne out in the data. However, although asset inequality does not appear to have a direct impact on the level of educational *inequality*, it does appear to have a role in *mobility.* Figure 7 shows that educational inequality has fallen most quickly over time in countries with the most egalitarian distribution of assets.

5 Estimation of the Inequality Accounting Formula

The second aspect of inequality considered in this paper is the elasticity of incomes to individual's human capital. Estimating the determinants of these educational returns, including the role of technological level and international trade, requires a two step process. The first step involves identifying the elasticities by conditioning income distribution data on the distribution of human capital, and the second lets these estimates can be conditioned on other variables. Estimating wages (as we will refer to the associated payments to human capital) is facilitated by hierarchical linear modeling techniques that allow the introduction of unobserved heterogeneity into the slope terms of the regression equation, allowing the latent wage coefficients to me modeled directly. The disadvantage, however, is that it requires drawing a great deal of distributional information out of a single piece of data – the income Gini coefficient – and thus relies heavily on the use of cross-country variation in identifying wage premiums and introduces a large number of conditioning variables, due to the numerous interactions, which will tend to generate large standard errors.

5.1 Estimation issues

The problems with using years of schooling to proxy for human capital have been demonstrated in the earlier analysis. Fortunately, the education returns in wages can be estimated without measuring human capital directly. If we assume that individuals attaining each level of education m, receive an associated wage w_m, we can nesting the Gini accounting equation (7) for $G(w)$ in the income inequality decomposition equation (4), so that we would estimate

$$G(y) = \alpha + \sum_{m=0}^{M} \beta_m D_m + \theta G(k) + \varepsilon \tag{11}$$

where $\beta_m = \frac{w_m}{\bar{y}}$ and $D_m = p_m \left[F_{m-1} - (1 - F_m) \right].$

Although equation (7) holds in principle for every country at every point in time, estimating the $M+1$ unknown wage coefficients in practice requires a set of $N \geq M+1$ observations. Standard regression techniques used for estimating the parameter vector $\mathbf{w} = \{\frac{w_0}{\bar{y}}, ..., \frac{w_M}{\bar{y}}\}$ from this set of observations assume that the country observations represent draws from the same statistical distribution. This assumption is suspect, however, since wages vary widely across countries and over time within countries.[23] Brock and Durlauf [9] discuss the prob-

[23] There is a range of evidence from growth regressions providing evidence of parameter heteroegeneity in cross-country regressions including Durlauf and Johnson [17], Kourtellos [25], and Durlauf, Kourtellos and Minkin [16].

lem of parameter heterogeneity in regressions within the context of the Bayesian notion of *exchangeability*.

A stochastic process is considered exchangeable when the joint probability measure of every finite collection of elements in the sequence is unaffected by permutations of the elements. In practice, we are interested only in exchangeability in the non-systematic (unmodeled) variation of our dependent variable. Specifically, conditional exchangeability implies (c.f., Bernardo and Smith [8]) that for every finite sequence of the stochastic process $\{\varepsilon_j\}_1^k$, given a conditioning set Θ, the probability measure μ, and an operator $\rho(\cdot)$ permuting the index j,

$$\mu(\varepsilon_1 = e_1, ..., \varepsilon_k = e_k|\Theta) = \mu(\varepsilon_{\rho(1)} = e_1, ..., \varepsilon_{\rho(k)} = e_k|\Theta) \tag{12}$$

In other words, the identity of the observation from which a given regression residual is taken should provide no additional information regarding its distribution. As Brock and Durlauf note, this is unlikely to be the case when observations are complex, heterogeneous objects like countries.

To estimate the vector $\mathbf{w}$ in a way that respects equation (12), requires we either limit our sample to those observations where we have reason to believe exchangeability will hold (the approach taken in Appendix B), or else model explicitly the variation in wages using a set Θ of country characteristics. An exhaustive set of conditioning variables would be difficult and statistically infeasible given the sample size, so attention is focused principally on those characteristics of interest in this paper – credit markets, government expenditures, and international trade.

It should be noted that estimating equation (11) directly is not possible, as the D_m variables together sum to zero. The regressions reported were estimated by dropping D_0 to avoid problems of perfect collinearity.[24] This requires that the coefficients be reinterpreted slightly. Since $D_0 = -\sum_{m=1}^{M} D_m$, the actual estimation is

$$\begin{aligned} G(y) &= \sum_{m=1}^{M} \beta_m D_m + \theta G(k) + \varepsilon \\ \text{with } \beta_m &= \left(\frac{w_m - w_0}{\bar{y}} \right) \end{aligned}$$

[24] The choice of D_0 was made for ease of interpretation of the coefficients as premia over "no education." However, the resulting estimates on w_m were largely the same when other D variables were dropped.

6 Hierarchical Modeling

There are several methods of accounting for parameter heterogeneity. One technique is to exploit natural hierarchical patterns in the data to decompose overall variation into components at different levels of the data structure. Random coefficient models used in panel data are one common example, however any systematic variation in the coefficients can also be modeled using interaction terms, and additional levels of hierarchy can be exploited as well when they exist. Bryk and Raudenbusch [10] provide details on the estimation of a three-level hierarchical linear (HL) model with the following general structure:

$$\begin{array}{rlr} Y_{ijk} = & \mathbf{X}_{ijk}\beta_{jk} + e_{ijk} & e_{ijk} \sim N(0,\sigma^2) \\ \beta_{jk} = & \mathbf{Z}_{jk}\pi_k + r_{jk} & r_{jk} \sim N(0,\Psi) \\ \pi_k = & \mathbf{W}_k\delta + u_k & u_k \sim N(0,\Omega) \end{array}$$

The variance in estimated coefficients at lower levels are modeled at higher levels using both deterministic and stochastic components. Recursive substitution of these equations leads to the following reduced form expression

$$Y_{ijk} = \mathbf{X}_{ijk}\mathbf{Z}_{jk}\mathbf{W}_k\delta + \mathbf{X}_{ijk}\mathbf{Z}_{jk}u_k + \mathbf{X}_{ijk}r_{jk} + e_{ijk}$$

which can be estimated as a mixed effects model with three separate variance components

$$\mathbf{Y} = \mathbf{A}_1\theta_1 + \mathbf{A}_2\theta_2 + \mathbf{A}_3\theta_3 + \mathbf{e} \tag{13}$$

where θ_1 represents the vector of fixed effects term (δ), θ_2 contains random effects that vary across the third level but not second ($\mathbf{u}$), and θ_3 is the random effects that vary across the second ($\mathbf{r}$). Dempster et.al. [14] discuss estimation of such models using the Expectation-Maximization (EM) algorithm.

6.1 On The Choice of Hierarchical Structure

In many applications of HL models the data hierarchy is clear (for instance, observations on students within classrooms within schools are used by Bryk and Raudenbush [10]). In the present situation, however, the choice of hierarchy must reflect the modeling considerations, questions of interest, and desire for parameter homogeneity. Previous work in a similar cross-country setting by Kourtellos (2001) has assumed that countries within regional (or income) groups can be treated much like individuals within schools, using repeated observations over time of each country. Unfortunately, the returns to education vary both geographically *and* temporally, which invalidates the traditional hierarchy. It is more appropriate, therefore, to use a statistical structure in which a sample of country observations are drawn at each point in time, among which systematic variation in wages occurs only at the region level.

The available evidence on wage premiums (e.g. from the OECD, and from background studies to the World Development Report, 1995) suggests it is more reasonable to assume that parameter estimates are drawn from the same distribution within the same region across countries at the same time period than within countries over time. There is a practical aspect to these structures as well: higher level conditioning variables such as per-capita output, private credit, and government education expenditures are not always available for all the countries in the initial sample, but regional estimates can be constructed from the countries with available data.

6.2 Estimation and Results

The HL model was constructed as follows. At the first level, the Gini accounting equation was estimated for 422 observations of countries at a point in time. At the second and third levels, eight regions were nested within four periods representing the decades from 1960 to 1970. The regions used are the same as those presented in Figure 1 with the exception that "North America" was expanded to a larger group denoted "English speaking" including the UK, Australia and New Zealand as well.

The table presented in Figure 8 summarizes the estimated fixed effects from the HL model. Standard errors are presented to the right of the point estimates, which are displayed in bold if their difference from zero cannot be rejected with a standard t-test at the 5% level. Given the number of parameters estimated (including the covariance terms in the errors) relative to the sample size, the general lack of significance is not entirely surprising. With the exception of the land Gini variable and the time trend, the covariates are all mean centered to preserve the interpretation of the level 1 regression equation. That is, the coefficient for the land Gini suggests an estimate of the asset income share $\hat{\theta} = .30$, increasing by an additional 0.06 each decade thereafter.

6.3 Investment constraints and wage inequality

There are three suggestive pieces of evidence from the hierarchical model regarding the role of investment constraints on equilibrium wages. It was shown earlier that government educational expenditure and private credit tend to reduce inequality in the distribution of skills in labor supply, and this appears to have a general equilibrium effect on wages as well. In the results in Figure 8, access to private credit is associated with a larger secondary education premium and a smaller higher education premium. Government educational expenditure has a similar effect, raising secondary education premiums and lowering higher education premiums. In section 4, it was shown that government spending had no clear impact on inequality in attainment among those receiving some education, but this evidence suggests that government educational policy in this area may be targeted toward higher education. This is consistent with Psacharopoulos [30], who has suggested that the government funding of education is regressive, biased towards subsidization of higher education. In short it appears that government spending and private credit both promote access to higher education and reduce

variable	MEAN	STD DEV	intercept Coeff	intercept SE	primary premium Coeff	primary premium SE	secondary premium Coeff	secondary premium SE	higher premium Coeff	higher premium SE
Land Gini	62.28	9.86	**0.300**	0.119						
Land Gini * time			**0.060**	0.025						
Urban	50.18	21.37	-0.049	0.084						
Property Rights	3.62	0.81	**6.413**	1.925						
intercept					0.198	*0.127*	0.319	*0.250*	-0.040	*0.397*
intercept * time					-0.032	*0.057*	**-0.240**	*0.116*	-0.052	*0.162*
Development index	33.34	26.01			0.002	*0.007*	0.002	*0.010*	-0.014	*0.017*
Develop. Index * time					0.002	*0.003*	0.002	*0.003*	-0.006	*0.005*
Gov. Ed.Expend/GDP	2.93	1.4			-0.019	*0.047*	**0.202**	*0.055*	**-0.290**	*0.108*
ln(years of schooling)	1.36	0.8			0.022	*0.142*	**-0.608**	*0.263*	-0.645	*0.616*
Private Credit	0.42	0.27			0.318	*0.341*	0.928	*0.535*	-0.188	*0.683*
Trade*LDC	34.11	23.75			**0.017**	*0.004*	0.010	*0.007*	-0.005	*0.014*
Trade*DC	22.29	27.37			0.002	*0.003*	-0.005	*0.004*	0.009	*0.007*

Figure 8: Results of the Hierarchical Linear Model

the associated wage premium. Controlling for these effects, additional increases in average years of schooling are correlated with only negligible changes in the primary premium, but large and significant decreases in the premium enjoyed by workers with both secondary and higher education. This too is consistent with closed economy general equilibrium effects in which wage premiums are determined by the relative scarcity of skill levels.

6.4 Globalization and Inequality

The Stolper-Samuelson Theorem in international trade has been interpreted, informally, as suggesting that trade helps to raise the return to abundant factors and lower the return to scarce factors. This suggests that countries rich in skill, capital and technology should see the returns to those factors rise – and thus the importance of the distribution of those factors in income inequality rise as well – while the opposite would occur in relatively more poor countries. Some anti-globalization protestors have asserted recently that economic integration is widening inequality in both developed *and* developing countries.

Although the latter proposition seems to contradict the standard Stolper-Samuelson prediction, recent work by Feenstra and Hanson [19] and Zhu and Trefler [37] shows that Northern industries following the flow of capital and technologies to the South can raise the demand for skill in both regions. In support of their theory, Zhu and Trefler point to a positive correlation between export growth and growth in income Gini coefficients among several developing countries during the 1980s. Zhu and Trefler focus their arguments on 29 lower-middle income countries during the 1980s. Expanding the sample reveals that the positive correlation exists primarily among developing countries with relatively more equal asset distributions.

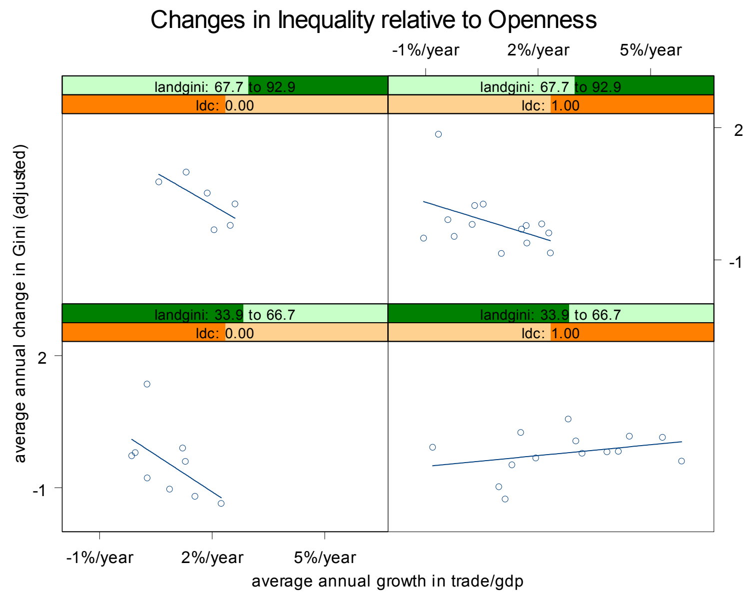

Figure 9: Growth in trade is associated with less growth in inequality, except in developing countries with a more equal distribution of assets.

Surprisingly, there is a clear negative correlation for industrialized countries, however, despite evidence based on more credible microeconomic studies that trade has had a small but positive impact on wage inequality in most OECD countries.

Unfortunately, like most trade theory, the Zhu-Trefler exercise treats income inequality and factor price ratios synonymously, without regard for movements in the factor distribution. It also treats "skill" as a binary variable. To properly ascertain the effects of trade on inequality in developing nations, the subject of study should be skill premiums rather than aggregate income inequality, and should allow the data to distinguish the relevant definition of "skill". These issues can be examined through the results in the hierarchical model. Ignoring for the moment the other conditioning factors to focus solely on the trade components of the wage equations, the estimated relationship in the HL model (Figure 8) employs an interaction with a dummy variable indicating less-developed (LDC) or developed (DC) country and estimates

$$w_k \propto \beta_1 \text{trade*LDC} + \beta_2 \text{trade*DC}$$

At the population level, this would estimate dual trade effects, β_1 when the indicator variable for the country being an LDC is equal to one, and β_2 when it is not. The actual conditioning takes place at the regional level, however, which in come cases includes both developed and developing countries. Nevertheless, under the maintained assumption that these β's do not vary within the first level of hierarchy, averaging the data should have no effect on the estimates. In the results presented, the impact of trade on the primary premium in LDCs is the only coefficient significant below the 5% level; however, the signs of all the estimates offer support for the basic Stolper-Samuelson logic. The impact of greater openness in industrialized countries is principally to raise the higher education premium and to lower the secondary education premium. The impact in developing countries is the opposite, however, raising the premium to workers with primary and secondary education and lowering it for workers with higher education. This suggests that more careful study of the role of trade in developing countries is warranted before economists and others dismiss Stolper-Samuelson effects entirely.

6.5 Social capital & Cultural effects

After controlling for the distribution and returns to human capital, it is possible to examine the "residual" inequality to search for factors that may affect income inequality through other channels. Two immediate possibilities are social capital and cultural values, which typically impact social structure and government policies. As a proxy for social capital we can use the share of the population in urban areas, which reflects the degree that members of the country may physically interact with each other on a day to day basis. Quantifying "cultural values" is clearly difficult, but an index of "respect for the ideal of private property" is one way to capture the notion that some societies value individual liberties – and thus presumably free market outcomes – more than others. The results in Figure 8 suggest that the percent in urban areas does not significantly affect inequality, although property rights do have a strong and significant role in explaining residual variance at the regional level. A one standard deviation increase in the property rights index is associated with an increase in the Gini coefficient of 5.2 (half of a standard deviation).

There are many other factors that can be addressed, although these are left for later work. The hierarchical modeling structure is convenient for the inclusion of such variables directly during estimation. The disadvantage is that they must enter at the regional, rather than the individual country level. For factors that may very significantly across the region, the income Gini can be conditioned on the human capital and wage conditioning variables alone, and then residuals used in further estimation in much the way that residuals from Solow growth accounting are used as a measure of total factor productivity.

7 Conclusion: Incomes and Outcomes

Previous research has data has studied *which* macroeconomic factors are associated with the Gini coefficient; this paper studies *how* these effects work, by decomposing aggregate inequality into that which can be attributed to the distribution of factor endowments and that which can be attributed to the relative price of those factors. The approach taken is a type of ecological inference: conditioning the marginal income distribution on the marginal distribution of human capital to estimate latent wage effects. While certainly not the only component of income inequality, the distribution of human capital is both a good starting point for understanding inequality, and important factor to account for before proceeding to more exotic explanations of inequality. Just as Solow accounting exercises help to establish the role of factor accumulation in growth, the study of income inequality should be conducted in a way that helps us understand the contribution made by factor distributions.

Researchers face two challenges in measuring human capital inequality: first, measures of human capital are themselves imprecise; second, the convenience of a single statistic to summarize a distribution is accompanied by a loss of information. I found that the Gini coefficient for years of schooling is quite sensitive to a measure of the private credit available in the economy as well as government education expenditures in the country. Unfortunately, the Gini coefficient for years of schooling does not exhibit a linear relationship with the income Gini as theory suggests for measures of human capital inequality. This is because measures of inequality based on years of schooling are dominated by the share of the population with no education, while income inequality is presumably dominated by the inequality of schooling among those educated. By employing a decomposition of educational inequality between the inequality between those with and without any education and the inequality among those with some education, a more accurate measure of the impact of schooling on inequality can be obtained. Employing this idea to re-evaluate the results of other research that has used years of schooling to measure educational inequality (e.g., Thomas et. al. [33]) could prove fruitful, since it may be that the results that have been attributed to *inequality* of education by these authors would be better interpreted as statements regarding *average* education ([23]).

To overcome the problems associated with proxies for human capital inequality, an accounting formula is developed that relates the income Gini solely to the distribution of education and the wage premium received at each level of education. Because wages are not observed, the formula presents multiple unknowns in a single equation. The latent wage effects can be estimated using cross-sectional variation in the inequality of income and education, but to satisfy the Bayesian notion of exchangeability, variance in the wage coefficients is modeled using a set of region-specific observable and unobservable factors, and estimated with a linear mixed effects model. This framework also allows tests of various hypotheses about the forces responsible for movements in wages, in particular the impact of trade. In contrast to suggestions that have been made using Gini coefficients alone, estimates from the hierarchical model support the conventional wisdom embodied in the Stolper-Samuelson theorem: trade is associated with a higher skill premium (return to education) in more developed regions and a lower skill premium in less developed regions. Growth of trade also appears to be negatively correlated with growth in aggregate income inequality in industrialized countries, and in developing countries with significant land inequality. One interpretation of the latter finding is that trade provides a vehicle of opportunity for the poor in countries with highly unequal asset distributions, perhaps by creating employment opportunities in export industries. Finally, the evidence suggests that higher levels of trade relative to GDP are associated with decreasing inequality over time – in both industrialized and developing countries – while closed economies have had, on the whole, relatively more persistent levels of income inequality.

This paper has offered some preliminary evidence on the larger question of how the equalization of the distribution of skills affects the distribution of economic outcomes, although there is clearly a need for additional and more detailed data. In general, however, increasing *opportunities* for educational investment – primarily in the form of access to credit markets – appear to result in both individually rising incomes and decreased overall wage inequality, which one might take as a vindication of Marshall's argument. The relative contribution of educational inequality to understanding income inequality appears to be most significant among the broad range of middle-income countries. In the poorest countries it is asset inequality (as proxied by land) that appears to be most significant in explaining income inequality, while among the OECD countries, it appears that other factors – perhaps the role of natural ability, which has been highlighted recently in the literature – are playing an increased role.

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A Factor Distribution and Prices in General Equilibrium

This paper demonstrates how, under some broad assumptions regarding individuals' incomes, the income Gini (measuring the size distribution of income) can be linked to the factor distribution and returns of human capital using an accounting relationship akin to (3). The strengths and weaknesses of such an approach are those of any accounting relationship. Unlike a regression motivated by theory, it has the advantage that it is "true" by definition, up to the validity of the identifying assumptions. On the other hand, since it relies on no particular economic model of distribution formation or wage determination, it does little to establish the causal forces and mechanisms generating inequality.

Thus, to establish a role for causation, an economic model explaining the distribution and returns to education is necessary. In theory these are both determined jointly in general equilibrium. In the interest of clarity, however, these two elements of inequality are examined one at a time. The determinants of both can be seen in the model that is sketched briefly below, in which the equilibrium distribution and returns to education depend on a country's asset inequality, private education costs, financial market quality, the marginal productivity gained from each level of schooling, and the elasticity of factor substitution embodied in the general state of technology.

A.1 Assets and education

Abstracting from exogenous differences in preferences or talents, heterogeneity in education choices can be traced to differences in households' budget constraints. Estimates by Psacharopoulos [30] of the private and social rates of return to schooling are, in most countries, well in excess of 8%, a reasonable estimate of the long-run rate of return to physical capital. This suggests that rational agents should in theory arbitrage as much physical capital for human capital as they are able. Nevertheless, huge disparities in educational achievement exist [**?**], and in much of the world sub-optimal levels of attainment still exist. In many cases, attainment is lowest where rates of return are highest, suggesting the presence of investment constraints rather than the absence of incentives.

Thus, in keeping with the apparent evidence, in the model below educational returns are assumed to be such that workers will each invest fully in education if they are able before acquiring capital savings. However, some are constrained from doing so. This idea has been introduced previously in the literature with the assumption that capital markets are imperfect, so that borrowing costs to finance individual's human capital exceeds the return on capital investment. Specifically, following Galor and Zeira [21], the relationship between interest paid on private household debt (r_b) and interest received from capital lending (r, reflecting the marginal product of capital in producing final output Y) is

$$r_b = \delta r \quad \text{where } \delta > 1$$

The premium, δ, may be the result of enforcement costs, or other transaction costs of going to formal loan markets. In the extreme case, it might be that borrowing is not possible at all ($\delta = \infty$) if, for instance, we interpret investment as being in *children's* education so that there is a problem of incomplete contracts. Regardless, with $\delta > 1$, the overall cost of financing educational investment is decreasing in an individual's wealth when educational costs exceed initial assets.

A.2 Household investment and asset accumulation

Consider an economy of n workers, indexed by i, that live for two periods. At birth, each worker is bequeathed a certain stock of capital assets, a_i. Workers have two investment technologies: direct savings placed in the capital market increase the worker's stock of capital assets in the next period by $(1+r)$, while educational investments in human capital h_i determine the second period wage $w(h_i)$. Human capital is acquired in period 1 through $M+1$ discrete levels of education indexed by $m = 0, ...M$. The cost of acquiring human capital of level h_m is $f(h_m)$.[25] The net capital market investment $k_i = [a_i - f(h_i)]$ may be positive or negative depending on whether the individual is a net lender or borrower in the first period. The choice of investment vehicles (physical or human capital) is made to maximize total net worth Q in the second period or

$$\max_{\{h\}} Q(h|a) = \begin{cases} [a - f(h)](1+r) + w(h) & \text{if } k \geq 0 \\ [a - f(h)](1+\delta r) + w(h) & \text{if } k \leq 0 \end{cases} \tag{14}$$

Let the optimal education choice for asset level a be $h^*(a)$. With log-linear preferences over consumption and bequests, a fraction ν of wealth is consumed in the second period, and the remainder is passed on to the next generation, generating a dynamic inter-generational path for wealth $a_{t+1} = (1-\nu)Q(h^*(a_t))$. If the gross rate of return to education $\phi(h) = \frac{w(h)-f(h)}{f(h)}$ satisfies $r \leq \phi(h) \leq r\delta$ for each h, then education financed through bequests is always more profitable than capital market investments, but arbitrage (i.e. borrowing on capital markets to finance investment in human capital) is profitable only on a small margin. It is further assumed that the net absolute return $w(h) - f(h)$ is increasing in h, so additional educational investment is always attractive.[26] These assumptions guarantee that the education ranking of the population will be the same as the income ranking in each period, since each is based on the ranking of initial assets.[27]

This result is useful for two reasons. First, it gives the conditions under which a range of socially-inefficient but individually optimal educational choices will occur. Second, it provides conditions under which the wage, education, income and wealth rankings are the same, which will later allow us to establish a relationship between the income Gini coefficient and the wage and/or education Gini coefficients.[28] Additionally, it is a necessary condition for multiple

[25] The specification of $f(h)$ admits interpretations as either financial costs (e.g., if $f(h) = fh$) or time, measured as the opportunity cost of lost wages (e.g., if $f(h) = hw(h_0)$. It is assumed that $f(h_0) = 0$, so that no education at no cost is always an option but returns some positive wage $w(h_0) = w_0 > 0$.

[26] This is not inconsistent with the evidence presented by Psacharopoulos [30] the rate of return $\phi(h)$ is falling, or with the assumption that $r \leq \phi(h) \leq r\delta$ for each h.

[27] There may be many levels of income within each educational level, since the distribution of assets is continuous and distribution of education is discrete. However, the statement is true in the following sense. If i denotes the ranking by incomes and e the ranking by education level, then $y(e) > y(e')$ if and only if $y(i) > y(i')$ for $i \in e$, $i' \in e' \neq e$.

[28] It does not hold for the ranking of capital income, however, since individuals who choose not to borrow for

steady states to occur in the individual income path (i.e., for a fixed point to exist in the dynamic path of assets). If we assume that preferences are such that $r < \left(\frac{\nu}{1-\nu}\right) < r\delta$ as well, the equilibria with positive saving – and only those equilibria – will be stable. As a result, multiple steady-state educational distributional exist depending on the distribution of wealth at some initial period.

The education distribution can be characterized as follows. Denoting the interest wedge $\Delta = (\delta - 1)r$, and the gross return by $R = (1 + r)$, then in each period borrowers choosing $h_m > h_{m-1}$ requires that $Q(h_m|a) \geq Q(h_{m-1}|a)$ or (for $\Delta > 0$)

$$a \geq f(h_m) - \frac{[w(h_m) - Rf(h_m)] - [w(h_{m-1}) - Rf(h_{m-1})]}{\Delta} \equiv c_m \tag{15}$$

likewise for lenders *not* choosing $h_{m+1} > h_m$ it must be that

$$a \leq f(h_{m+1}) - \frac{[w(h_{m+1}) - Rf(h_{m+1})] - [w(h_m) - Rf(h_m)]}{\Delta} \equiv c_{m+1} \tag{16}$$

Therefore, if assets are distributed over the population according to $\Psi(a)$, then the share of the population p_m with each education level m can be expressed

$$p_m = \Psi(c_{m+1}) - \Psi(c_m) \tag{17}$$

The prediction embodied in equations (17), (15) and (16) is that the distribution of human capital will depend on the distribution of assets $\Psi(a)$, the "investment surplus" over financial assets of each education level, $w(h) - Rf(h)$, and the degree of credit constraints, Δ. A higher (lower) skill premium for a given level of education will lead to a larger (smaller) share of the population choosing that particular level of education, while the credit market interest rate wedge (Δ) lowers both c_m and c_{m+1}, which will reduce overall education attainment for any given distribution of assets.[29]

A.3 Production Sector and Factor Price Determination

The second link in our exploration of inequality, between inequality of human capital and inequality of incomes, depends on the structure of labor demand. Suppose that national output, Y, is produced under constant returns using both types of capital inputs (physical and

additional education will invest their remaining assets, but this will not directly effect the empirical strategy. Nevertheless, the accumulation of capital is not sizeable until after the individual has invested in the highest feasible level of human capital. In the PSID data, those with significant capital income tend to have either very high or very low earnings (e.g., those living off of trust funds), but conditioning on labor force earnings , the probability of having a high capital income is only significant for those with very high labor incomes.

[29] Among other things, this suggests that the ratio of the human to physical capital stock $(\bar{h}/\bar{k})$ is a useful indicator of the impact of credit constraints in education.

human) or[30]

$$\begin{aligned} Y &= Y(H_0, H_2, ..., H_M, K) \\ \text{where} \quad H_m &= h_m L_m \qquad m = 0, ..., M \\ \text{and} \sum\nolimits_m L_m &= L \end{aligned}$$

L_m represents the size of the labor force with a particular level of schooling m, and h_m indexes the marginal productivity of that labor in output. All labor at a certain education level is considered homogenous, so there is no within-group earnings inequality. Individual i's second period income reflects the factor returns to the inputs she has supplied in production, or[31]

$$y(i) = w_{m(i)} + rk(i) \tag{18}$$

where $r = \frac{dY}{dK}$, and $w_m = \frac{dY}{dL_m} = \left(\frac{dY}{dH_m}\right) h_m$. Thus, by national income accounting, per-capita income μ is given by

$$\mu = \sum_{m=1}^{M} w_m p_m + \frac{rK}{L}$$

This highlights the two principal factors determining how changes in the distribution of educational attainment are passed through to the distribution of incomes. The first is the actual productivity of education (h), and the second is the elasticity of demand for particular types of human capital (embodied in the term $\frac{dY}{dH_m}$). If education has little productive value or if the demand for more skilled labor is highly inelastic, then increases in educational attainment throughout the workforce may not translate into higher wages. In the data, the technology embodied in the production function (in particular, the elasticity of output with respect to human capital) will affect the share of national income accruing to each level of education. That is, the income share $s_m \equiv \frac{w_m L_m}{Y} = \left(\frac{dY}{dH_m}\right) \frac{H_m}{Y}$, the elasticity of output with respect to human capital type m. If we denote this elasticity by θ_m, then this means factor prices, $w_m = \frac{\theta_m}{p_m}\mu$.

A.4 Empirical implementation

In general equilibrium, both the distribution of education and the educational premium reflected in wages will depend on the primitive model parameters. The table below lists the proxies used for each of the model parameters in the empirical work in the paper. Although

[30] This structure generalizes a number of different specifications of human capital employed in the literature, including both the traditional two capital good model (which treats H analogously to physical capital) and models with imperfect substitutability between "skilled" and "unskilled" labor in production.

[31] Note the distinction between income y and net worth Q defined in the previous section. Although the latter corresponds more closely to welfare, the focus on the former is due to its correspondance with the income concept measured in the data. The distinctions mainly involving debt financed investment (for example, interest is included in income, but borrowing costs are often treated as a household expenditure).

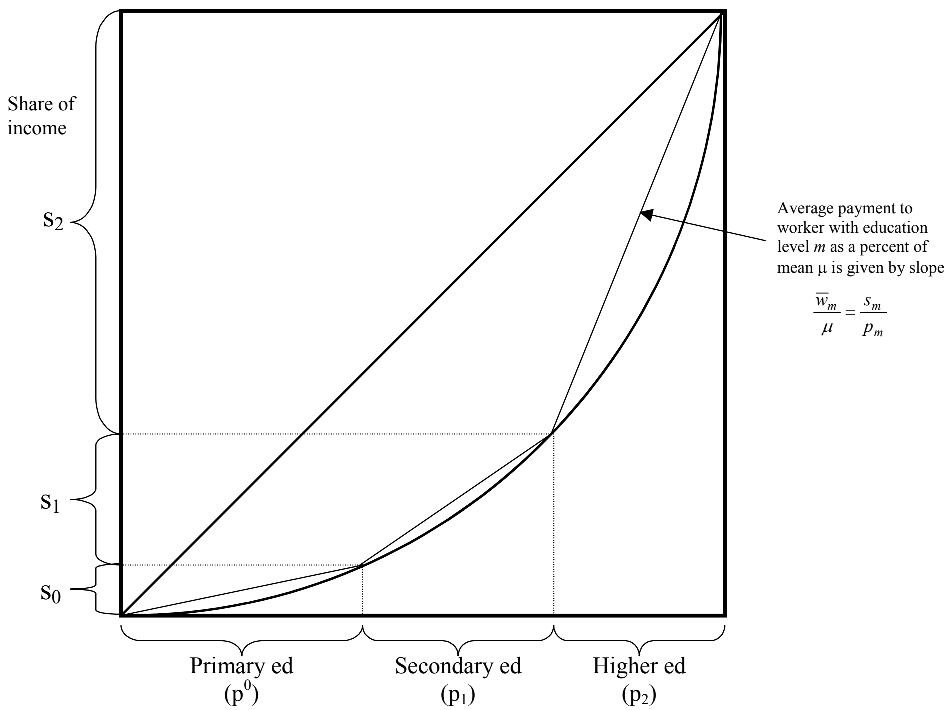

Figure 10: In theory, education leads to higher incomes. This ordering allows the use of Lorenz curve data to identify relative rates of return to education.

the model allowed capital market flows, for simplicity there was no introduction of international trade. Clearly, trade may have an important role in the skill-composition of labor demand in the real world, however.

parameter	meaning	empirical proxy
$F(a)$	asset distribution	land gini
$\mathbf{f}(\mathbf{h})$	private cost of education	government ed. expenditure
Δ	borrow/lend wedge	availability of private credit
$\boldsymbol{\alpha}$	technology	per-capita income
	degree of trade	(exports+imports) / GDP

B Trends in the Returns to Skill

The table in Figure 11 reports the estimated coefficients and standard errors for 4 broad levels of education. The pooled sample of 274 observations with income, education, and land inequality data was partitioned into six sub-samples by level of development and time period. The first three rows of the table list the average levels of educational attainment within each group, the next set of rows present the regression estimates (the $\beta's$) and their standard errors, reflecting the "skill premia" as a percentage of per-capita GDP, $\frac{w_m - w_0}{\mu}$. From these coefficients the next set of rows back out estimates of wages as a percentage of GDP, $\frac{w_m}{\mu}$.

The results suggest that the returns to primary and secondary education have fallen sharply in industrialized countries while rising slightly in developing countries. The return to higher education has risen in industrialized countries and fallen in developing countries. Overall, the relative importance of education appears to be greater in industrialized than developing countries, as movements in the income Gini appear to be dominated by non-wage sources of inequality in the latter. In particular, the role of inequality of land appears to be much larger, as would be expected in developing countries.

B.1 A hypothesis explaining the time-series persistence of the Gini Coefficient

The results in the previous section suggest the following stylized facts: educational attainment is increasing in both industrialized and developing countries, but the premium to higher levels of education appears to be rising in industrialized countries (suggesting skilled labor demand is outpacing supply) and falling in developing countries (suggesting skilled labor supply is outpacing demand). The following simple model illustrates how these trends are consistent with a stable Gini coefficient.

Suppose there are types of labor: skilled (receiving y_H) and unskilled (receiving income y_L), with $y_H > y_L$. Define $\pi \equiv \frac{y_H - y_L}{y_L}$ as the skill premium. If a fraction λ of the population is skilled, then using our accounting equation (7) suggests the Gini coefficient can be written

	Industrialized Countries			Developing Countries		
	1970s	1980s	1990s	1970s	1980s	1990s
Primary share	50.1	40.8	35.1	45.5	43.1	38.0
Secondary share	32.8	38.6	41.6	11.1	17.9	24.5
Higher share	9.3	13.8	17.7	2.8	4.8	7.3
Primary premium	0.97	0.30	0.23	0.73	0.92	0.61
SE	*0.34*	*0.23*	*0.38*	*0.17*	*0.16*	*0.18*
Secondary premium	2.05	0.99	0.82	0.54	1.37	0.53
SE	*0.45*	*0.26*	*0.43*	*0.37*	*0.24*	*0.38*
Higher premium	1.78	1.35	1.47	1.95	1.46	0.77
SE	*0.56*	*0.34*	*0.54*	*0.71*	*0.39*	*0.44*
Land Gini	0.16	0.21	0.17	0.45	0.30	0.52
SE	*0.08*	*0.05*	*0.09*	*0.06*	*0.06*	*0.08*
sum(beta*p)	1.32	0.69	0.68	0.45	0.71	0.42
est w0	-0.48	0.10	0.15	0.11	-0.01	0.06
est w1	0.48	0.40	0.38	0.83	0.91	0.67
est w2	1.57	1.09	0.97	0.65	1.36	0.60
est w3	1.30	1.45	1.62	2.06	1.45	0.83
Mean G(y)	36.1	33.8	33.3	42.9	38.6	42.3
sum(beta*D)	27.1	20.8	22.9	14.3	23.0	9.0
Pred. G(w)	32.2	26.3	27.5	25.9	32.7	18.7
other inequality	9.0	13.0	10.4	28.7	15.7	33.3

Figure 11: The first three rows present the average distribution of educational attainment by period and income group, revealing similar changes between industrialized and developing countries. Coefficient estimates in the next rows can be reinterpreted as education-specifc wages w_m/μ as a ratio of per-capita income. The final rows suggest that the ability of movements in the educational distribution and returns to explain changes in overall inequality is greater for industrialized countries. Land inequality plays a larger role in developing countries.

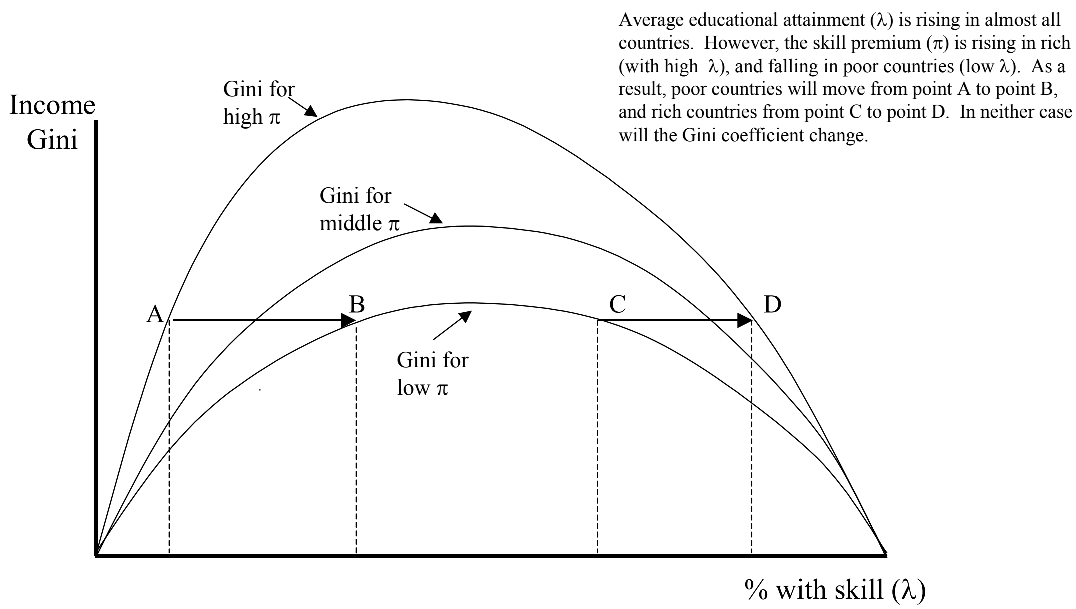

Figure 12: A graphical description of one hypothesis of why Gini coefficients do not appear to be correlated with the distribution of education over time.

as

$$Gini = \frac{(y_H - y_L)}{\mu}\lambda(1-\lambda) = \frac{\lambda(1-\lambda)}{\lambda + \pi^{-1}}$$

For a given level of the skill premium, this can be graphed as a concave function λ, as depicted in Figure 12. If the skill premium is falling with educational attainment at low levels of λ, and rising with attainment at high levels of λ, as the evidence suggests, then the Gini coefficient will remain relatively stable over time.

Clearly there are more dimensions to "skill" than a simple binary framework can allow. Returning to the estimation results reported above, however, there does appear to be some evidence for this effect. Figure 13 highlights inequality trends by educational level aggregate Gini changes, summarizing the distributional (first row) and estimated price (second row) effects reported in Figure 11.[32] The results suggest that from the 1970s to 1990s, the majority of the average fall in inequality in the industrialized world was due to expansion of secondary education and the associated fall in the premium to secondary education, which led to greater equalization of wages among the majority of the population. The table also reveals that although the dual trends of rising college wage premia and attainment of higher

[32] The negative values of the D_m variables are due to the weighting function $a(i) = i - \frac{n+1}{2}$ used in the Gini coefficient. The weights placed on values of the variable below the median are negative, and the weights placed on values above the median are positive.

Industrialized Countries

	no ed. D0	prim. D1	sec. D2	higher D3
1970/75	-5.69	-15.71	13.47	7.93
1980/85	-5.42	-16.55	10.85	11.12
1990/95	-4.87	-16.90	8.16	13.61

	w0	w1	w2	w3
1970/75	-0.48	0.48	1.57	1.30
1980/85	0.10	0.40	1.09	1.45
1990/95	0.15	0.38	0.97	1.62

	w0*D0	w1*D1	w2*D2	w3*D3	G(w)
1970/75	2.7	-7.6	21.1	10.3	27
1980/85	-0.5	-6.6	11.8	16.2	21
1990/95	-0.7	-6.4	7.9	22.0	23

Developing Countries

	no ed. D0	prim. D1	sec. D2	higher D3
1970/75	-17.21	6.21	8.32	2.68
1980/85	-16.75	0.80	11.50	4.46
1990/95	-14.37	-3.08	11.03	6.42

	w0	w1	w2	w3
1970/75	0.11	0.83	0.65	2.06
1980/85	-0.01	0.91	1.36	1.45
1990/95	0.06	0.67	0.60	0.83

	w0*D0	w1*D1	w2*D2	w3*D3	G(w)
1970/75	-1.8	5.2	5.4	5.5	14
1980/85	0.2	0.7	15.6	6.4	23
1990/95	-0.9	-2.1	6.6	5.4	9

Figure 13: Sample averages of the human capital distributional component of the Gini coefficient (top row) and estimates of the wages by education level (middle row) can be used to assess total contribution to measured inequality (bottom row).

education have been a force generating inequality for some time, it only began to dominate the inequality statistics in the 1990s, when attainment reached a sufficiently high level.

In developing countries, however, rising attainment of higher education has been met with concurrent falls in the premium to higher education, causing little net impact on aggregate income inequality. The most important trend has been at the primary level, where distributional and price changes have helped lower inequality systematically since the 1970s. Although this trend is dominated in the 1980s by a sudden spike in the return to secondary education, it is quite possible that this reported movement is largely or in part a statistical artifact of the data, the identification assumptions, and/or the estimation procedure.

This exercise helps to understand patterns of income inequality movements across a wide range of countries, but some caution is clearly warranted in interpretation. The trends are broadly consistent with evidence from microeconomic earnings studies, but no structure so simple can hope to explain accurately the breadth of inequality experiences across all countries. On the whole, it is likely that estimates for the industrialized countries are more reliable than those for developing countries, since they tend to be a more homogeneous group. On the other hand, the assumption that wages vary only by education is likely to be more questionable among the OECD countries, where within-group inequality has been shown to represent a substantial portion of overall inequality.