DISTRIBUTIONAL GROWTH ACCOUNTING: EDUCATION AND THE REDUCTION OF GLOBAL POVERTY, 1980-2019*

AMORY GETHIN

July 8, 2025

Abstract

This article quantifies the role played by education in the reduction of global poverty. I propose tools for identifying the contribution of schooling to economic growth by income group, integrating imperfect substitution between skill groups into macroeconomic growth decomposition. I bring this "distributional growth accounting" framework to the data by exploiting a new microdatabase representative of nearly all of the world's population, new estimates of the private returns to schooling, and historical income distribution statistics. Education can account for about 45% of global economic growth and 60% of pretax income growth among the world's poorest 20% from 1980 to 2019. A significant fraction of these gains was made possible by skill-biased technical change amplifying the returns to education. Because they ignore the distributional effects of schooling, standard growth accounting methods substantially underestimate economic benefits of education for the global poor.

JEL: D31, O11, I24, I25, I26.

*I am particularly grateful to Thomas Piketty, Vincent Pons, Emmanuel Saez, and Gabriel Zucman for their continuous guidance. I thank the editors, Lawrence Katz and Andrei Shleifer, five anonymous referees, as well as Daron Acemoglu, Pierre Bachas, Denis Cogneau, Eva Davoine, Jérémy Do Nascimento Miguel, Sebastian Hager, Eric Hanushek, Hilary Hoynes, Anders Jensen, Pete Klenow, Karen Macours, Giulia La Mattina, Ségal Le Guern Herry, Wouter Leenders, David Levine, Antoine Levy, Hongbin Li, Rosanne Logeart, Nicolas Longuet Marx, Clément Mazet-Sonilhac, Edward Miguel, Mathilde Muñoz, Emi Nakamura, Jon Piqueras, Tom Raster, Anne-Sophie Robilliard, Benjamin Schoefer, Jón Steinsson, Christopher Walters, Duncan Webb, Danny Yagan, Céline Zipfel, and many conference and seminar participants for useful comments. I also thank the International Labour Organization for giving me access to data tabulations from their collection of harmonized household surveys; I am especially thankful to David Bescond for his help and assistance throughout. Juan Ferrer provided excellent research assistance. This research benefited from funding from the Paris School of Economics (Grant ANR-17-EURE-001). The findings, interpretations, and conclusions expressed in this paper are entirely those of the author. They do not necessarily represent the views of the International Bank for Reconstruction and Development/World Bank and its affiliated organizations, or those of the Executive Directors of the World Bank or the governments they represent.

I. Introduction

The past decades witnessed major improvements in access to public services in developing countries. These improvements were evident in progress made on indicators as diverse as school enrollment, healthcare coverage, and access to drinkable water (United Nations, 2023).

How useful these policies have been at generating income growth for the global poor remains an open question. Education, in particular, has expanded massively, yet its contribution to global poverty reduction remains unclear. The economic effects of education depend on who gets access to schooling, the returns to schooling, and general equilibrium effects. Because of difficulties in quantifying these channels, we lack estimates of the benefits of schooling for the global poor. Addressing this gap is of fundamental importance for policy, in a world where the majority of children from low-income households are enrolled in public schools.

This article estimates the aggregate and distributional effects of worldwide educational expansion from 1980 to 2019. Leveraging a new microdatabase on individual incomes, a "distributional growth accounting" model of education and the wage structure, and complementary quasi-experimental evidence, I quantify the contribution of schooling to growth for different groups of the world distribution of income. I find that education accounts for a substantial fraction of global economic growth and extreme poverty reduction during this period, placing education policies at the forefront of economic progress.

The starting point is a new microdatabase representative of 97% of the world's population based on household surveys fielded in 154 countries around 2019 collected from data repositories and country-specific sources. Each survey provides information on individual incomes, education, age, gender, and other socioeconomic variables. I harmonize each survey to construct a single dataset covering 10 million surveyed individuals, providing a comprehensive microdatabase to analyze the contemporary structure of global poverty and inequality.

Starting from this new dataset, I develop methods to estimate what the world distribution of income would have looked like in 2019 had schooling not improved since 1980. I combine standard growth accounting tools with a model of education and the wage structure *à la* Goldin and Katz (2007). In this "distributional growth accounting" framework, expanding education raises aggregate labor income by the private return to schooling, which is endogenous to relative supply (education) and relative demand (the skill bias of technology) for skilled labor. Schooling also reduces inequality by lowering the relative wage of skilled workers as their supply increases.

The model delivers three main results. First, the contribution of education to growth is larger than in a standard growth accounting decomposition. The return to schooling would be higher today had education not expanded, because the supply of skilled workers would be lower. As a result, reverting education to its 1980 levels would imply a greater loss in output than what 2019 returns to schooling suggest. Second, education disproportionately benefits low-income earners: inequality would be higher had the relative supply of skilled workers not increased. Third, the total effect of education on growth can be decomposed into two forces: the "independent" effect that education would have had if labor demand had not changed, and skill-biased technical change, which raises the returns to schooling by increasing relative demand for skilled labor.

I begin by estimating the total contribution of education to global poverty reduction. I construct a counterfactual world distribution of income in three steps. First, I downgrade education levels in each survey until matching the 1980 distribution of educational attainment. Second, I reduce individual incomes accordingly, combining new country-specific estimates of returns to primary, secondary, and tertiary education with supply effects derived from the model. Third, I compare the resulting counterfactual to the actual evolution of incomes, yielding an estimate of the contribution of education to growth for different groups within each country.

I find that private returns to schooling account for about 45% of global economic growth (40-65% depending on the specification) and 60% (50-100%) of pretax income gains among the world's poorest 20% over 1980-2019 (see Figure I). Education also explains about one-third of the reduction in the share of the world's population living in extreme poverty.

A natural concern with this analysis is that private returns to schooling may differ from the aggregate effects of education on growth. This framework may also miss important channels through which education affects the income distribution. To address these limitations, I validate my approach with new quasi-experimental evidence by extending existing work on three large-scale schooling initiatives in India (Khanna, 2023), Indonesia (Duflo, 2001), and the United States (Acemoglu and Angrist, 2000). Combining microdata on the distribution of income with differential exposure to each program across subnational regions, I document two facts. First, educational expansion had large causal effects on aggregate regional incomes, comparable to individual returns found in the same contexts. Second, all three policies disproportionately benefited low-income earners. The distributional growth accounting framework accurately replicates these two findings, suggesting that it provides a good methodological foundation to study the role of education in shaping the distribution of income growth.

More generally, my estimates should be considered conservative. My main specification relies on standard Mincerian returns, which are typically lower than causal estimates as I show in a new meta-analysis of 62 papers. I assume that education only affects labor income, excluding positive effects on physical capital and human capital externalities, on which there is now significant empirical evidence (e.g., Moretti, 2004; Gennaioli et al., 2013; Guo, Roys, and Seshadri, 2018; Queiró, 2022). My findings end up depending on three sets of parameters: the private returns to schooling, the degree of imperfect substitutability between skill groups, and the extent to which other production factors adjust. With plausible bounds for these parameters, education is found to account for 50% to 100% of growth among the world's poorest 20%.

Methodologically, accounting for distributional effects of schooling within countries appears essential. Standard growth accounting, as in Barro and Lee (2015), typically combines cross-country data on years of schooling with a constant 10% return to conduct the same exercise as in this paper. This approach could provide a good approximation. I find that it does not: education accounts for 16% of growth among the world's poorest 20% with this method, compared to 58% in my benchmark specification.[1] One reason is that global poverty cannot be measured accurately from cross-country data: the poorest individuals in the world do not all live in the poorest countries. The global poor also rely more on labor income and thus benefit more from education. Most importantly, standard growth accounting does not account for supply effects: had education not improved, incomes would be lower than what 2019 returns to schooling imply, and that of low-skilled workers disproportionately so. The contribution of this paper lies in the use of new microdata and tools to quantify each of these channels.

I conclude by analyzing the role of skill-biased technical change in amplifying the returns to schooling, exploiting additional surveys fielded around 2000 in 109 countries representing 80% of the world's population. In the average country, about 30% of the benefits of education from 2000 to 2019 were made possible by skill-biased technical change. There is substantial heterogeneity across countries, however: demand for skilled labor increased rapidly in high-income countries while it stagnated in the developing world. Taking stock of this evidence, I estimate that skill-biased technical change can explain up to 30% of aggregate economic growth, but less than 5% of growth among the world's poorest 20% during this period.

A large literature in labor economics uses the canonical labor supply-and-demand framework to relate

[1] The standard approach also underestimates the contribution of education to aggregate growth by about 30%, for two main reasons. First, it implicitly assumes that the return to schooling only applies to a fraction of mixed income, while I provide evidence that mixed income is affected by education just as much as wages. Second, I account for imperfect substitution, which increases the contribution of schooling by magnifying losses from not expanding education.

changes in the wage distribution to educational expansion.[2] Concurrently, a considerable literature in macroeconomics investigates the contribution of human capital to economic development.[3] These two methodological perspectives, one focused on within-country inequality and the other on cross-country dynamics, have remained relatively independent from one another. The main contribution of this article is to unify them into a "distributional growth accounting" framework, which I use to quantify the role played by education in the reduction of global poverty.

This article also contributes to our understanding of the forces shaping the long-run evolution of the world distribution of income. Global inequalities have undergone major transformations in recent decades, including rapidly declining poverty and cross-country income convergence (Sala-i-Martin, 2006; Chen and Ravallion, 2010; Pinkovskiy and Sala-i-Martin, 2016; Hammar and Waldenström, 2020), the emergence of a new "global median class" (Lakner and Milanovic, 2016), and skyrocketing top income inequality (Chancel and Piketty, 2021). Amongst the many drivers shaping these dynamics, I isolate the contribution of one of them: education.

Finally, this paper relates to an extensive empirical literature on the economic effects of education. Many studies document positive impacts of schooling on individual earnings (Card, 2001; Psacharopoulos and Patrinos, 2004; Deming, 2022). A more limited number of studies examine the general equilibrium effects of education policies (e.g., Duflo, 2004; Porzio, Rossi, and Santangelo, 2022; Hsiao, 2023; Khanna, 2023). I complement this evidence by revisiting the impact of education on growth and inequality in three different contexts. I also draw extensively on the literature to calibrate the parameters guiding my results, such as elasticities of substitution and returns to schooling, in line with recent efforts at bridging the micro-macro gap in the study of development (Buera, Kaboski, and Townsend, 2023).

The rest of the paper is organized as follows. Section II outlines the conceptual framework. Section III presents the data and methodology. Section IV describes the main results. Section V studies the role of skill-biased technical change in amplifying the benefits of education. Section VI concludes.

II. Distributional Growth Accounting

This section develops the distributional growth accounting framework. Section II.A presents the model specification. Sections II.B and II.C discuss how to estimate the contribution of education to aggregate

[2]This framework has been extensively applied to study wage inequality in the United States (e.g., Katz and Murphy, 1992; Goldin and Katz, 2007; Goldin and Katz, 2008; Murphy and Topel, 2016; Autor, Goldin, and Katz, 2020). A growing literature extends this analysis to low- and middle-income countries (Fernández and Messina, 2018; Vu and Vu-Thanh, 2022; Khanna, 2023).

[3]The recent literature focuses on development accounting (e.g., Hall and Jones, 1999; Hsieh and Klenow, 2010; Gennaioli et al., 2013; Jones, 2014; Hendricks and Schoellman, 2018). Growth accounting dates back to Solow (1957), although worldwide perspectives are more recent (Mankiw, Romer, and Weil, 1992; Barro and Lee, 2015; Ahmed et al., 2020; Collin and Weil, 2020).

growth and its distribution within countries in this model.

II.A. *Model Specification*

Output per capita at time t is produced from per-capita physical capital K^t and labor H^t:

$$Y^t = F(K^t, H^t) = K^{t\alpha}(z^t H^t)^{1-\alpha} \tag{1}$$

Where z^t denotes total factor productivity. Labor input per capita is a CES aggregator of the form:

$$H^t(\theta^t, L^t) = \left(\theta_1^t L_1^{t\,\frac{\eta-1}{\eta}} + \theta_2^t L_2^{t\,\frac{\eta-1}{\eta}}\right)^{\frac{\eta}{\eta-1}} \tag{2}$$

L_1^t and L_2^t are the shares of low-skilled and high-skilled workers. θ_1 and θ_2 are factor-augmenting technology terms. η is the elasticity of substitution between low-skilled and high-skilled workers, assumed to be greater than 1. Taking logs, the change in output per capita between two time periods can be decomposed into the contributions of physical capital, total factor productivity, and human capital:

$$\Delta \ln Y = \alpha \Delta \ln(K) + (1-\alpha)\Delta \ln(z) + (1-\alpha)\Delta \ln(H) \tag{3}$$

The share of output growth accounted for by each input is given by:

$$1 = \underbrace{\frac{\alpha \Delta \ln(K)}{\Delta \ln Y}}_{\text{Physical Capital}} + \underbrace{\frac{(1-\alpha)\Delta \ln(z)}{\Delta \ln Y}}_{\text{TFP}} + \underbrace{\frac{(1-\alpha)\Delta \ln(H)}{\Delta \ln Y}}_{\text{Education + Skill Bias}} \tag{4}$$

II.B. *Aggregate Effect of Education*

In equation 4, the change in the labor aggregator $\Delta \ln(H)$ results from the combination of two non-additive forces: changes in relative demand for skilled workers θ (skill-biased technical change) and changes in their relative supply L (educational expansion). Accordingly, there are several ways of evaluating the contribution of education to growth, corresponding to different counterfactual questions.

Total versus Independent Effects of Education A first consideration relates to the level of technology θ at which the contribution of education is evaluated. As highlighted by Caselli and Ciccone (2019) and Hendricks and Schoellman (2023), the effect of education is not uniquely determined when skilled labor and the skill bias of technology are complements: it depends on the reference technology level at which it is evaluated. In our context, one option is to estimate the contribution of education to growth given the skill bias of technology observed in 2019:

$$\text{Share}_{\text{L}}^{\theta^{2019}} = (1-\alpha)\frac{\ln H(\theta^{2019}, L^{2019}) - \ln H(\theta^{2019}, L^{1980})}{\ln Y^{2019} - \ln Y^{1980}} \tag{5}$$

I refer to this as the "total" contribution of education, corresponding to the following counterfactual question: how much lower would growth have been if education had not improved, but skill-biased technical change had evolved the way it has? Alternatively, one may evaluate the effect of education given the technological skill bias observed in 1980:

$$\text{Share}_{\text{L}}^{\theta^{1980}} = (1-\alpha)\frac{\ln H(\theta^{1980}, L^{2019}) - \ln H(\theta^{1980}, L^{1980})}{\ln Y^{2019} - \ln Y^{1980}} \tag{6}$$

I refer to this as the "independent" contribution of education. The corresponding counterfactual question is: what would have been the contribution of education to growth absent skill-biased technical change? In the presence of technological change, we should expect demand for skilled labor to grow over time: $\Delta\theta_2 > \Delta\theta_1$. As a result, the total effect of education is typically greater than its independent effect: the quantitative importance of education is maximized when evaluated at $\theta = \theta^{2019}$ and minimized when evaluated at $\theta = \theta^{1980}$. The difference between the two estimates captures an interaction term between education and technology, which reflects the role played by labor demand in amplifying the returns to schooling.

Short-Run versus Long-Run Elasticities A second consideration relates to how education and technology affect each other. The previous decomposition identifies the effect of education holding technology fixed. In practice, however, labor supply and labor demand may endogenously respond to each other.

On the one hand, labor demand may respond to educational expansion. I consider the endogenous technological choice model of Hendricks and Schoellman (2023). Formally, let firms choose the optimal skill weights θ_1^t and θ_2^t under the constraint of a technology frontier, as in Caselli and Coleman (2006):

$$\left(\kappa_1^t {\theta_1^t}^{\omega} + \kappa_2^t {\theta_2^t}^{\omega}\right)^{\frac{1}{\omega}} \leq 1 \tag{7}$$

We assume that $\omega - \frac{\eta-1}{\eta} - \omega\frac{\eta-1}{\eta} > 0$. Hendricks and Schoellman (2023) show that solving for the firm's optimal skill bias yields a reduced-form aggregator of the form:

$$H^t(A^t, L^t) = \left(A_1^t L_1^{t\,\frac{\sigma-1}{\sigma}} + A_2^t L_2^{t\,\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{8}$$

Where $\sigma > \eta$ and the technology parameters A_j are exogenous. In other words, allowing firms to choose their technological mix is theoretically equivalent to increasing the elasticity of substitution while holding the skill bias of technology fixed. η is a short-run elasticity of substitution, corresponding to the degree of imperfect substitutability observed when firms take technology as given. σ is a long-run elasticity, reflecting the fact that firms adjust their labor demand as a response to educational expansion. Using a long-run elasticity is thus equivalent to modeling technical change as indirectly resulting from education.

On the other hand, educational choices may themselves be shaped by skill-biased technical change. A large literature documents the role played by the economic environment in shaping schooling decisions (e.g., Edmonds, Pavcnik, and Topalova, 2010; Restuccia and Vandenbroucke, 2013; Atkin, 2016). Unfortunately, quantifying this channel is not possible in the absence of surveys fielded in the 1980s, which would be necessary to estimate the degree to which schooling responds to labor demand.[4] Throughout the paper, I treat education as exogenous and leave the study of the determinants of schooling for future research.

Interpretation and Comparison with Standard Growth Accounting How do these methodological choices affect growth accounting estimates and why? In the standard growth accounting exercise, human capital is a function of a fixed return to schooling, such as 10% per year of education. With imperfect substitution, in contrast, the return to schooling is endogenous:

$$\ln\left(\frac{w_2^t}{w_1^t}\right) = \ln\left(\frac{A_2^t}{A_1^t}\right) - \frac{1}{\sigma}\ln\left(\frac{L_2^t}{L_1^t}\right) \tag{9}$$

The return to schooling is increasing in relative demand for skilled workers (the skill bias of technology) and decreasing in their relative supply (education). This relationship has three implications.

First, the total contribution of education is greater than in the standard exercise. The intuition is the following: the return to schooling would be higher today if education had not improved, because the relative supply of skilled workers would be lower. As a result, the decline in output that would arise from bringing

[4] In section V, I provide evidence that skill-biased technical change has been limited in developing countries since 2000, however, which suggests that this channel has been modest at least during this period.

education back to its 1980 level is larger than what returns to schooling observed today suggest.[5]

Second, this contribution is maximized at lower values of the elasticity of substitution. Using a lower elasticity is equivalent to assuming that firms would not adjust their technological mix if education came back to its 1980 level, which generates a much larger decline in output in the counterfactual.

Third, the difference between the independent and total contributions of education is lower for higher values of the elasticity of substitution. Intuitively, choosing a higher elasticity amounts to interpreting skill-biased technical change as resulting from educational expansion, which limits the role played by exogenous technological change in shaping the returns to schooling. Conversely, using a lower elasticity implies that the total effect of education is larger, but also that a larger fraction of this total effect results from an interaction term between education and technology.

Roadmap In summary, I consider in this paper two sets of specifications depending on (1) the level of technology at which the effect of education is evaluated and (2) whether skill-biased technical change is interpreted as resulting from educational expansion (long-run elasticity) or not (short-run elasticity). Section IV starts by presenting results on the total effect of education, that is, the effect of education evaluated at $A = A^{2019}$. This counterfactual can be precisely estimated for the world as a whole, since it only requires data on education and earnings in 2019. I then turn to the independent contribution of education in section V. This second exercise requires estimating skill-biased technical change, which necessitates historical surveys fielded at the beginning of the period of interest. Such surveys do not exist for the 1980s, but I was able to mobilize additional sources to do so for a more restricted sample of countries since 2000.

II.C. Distributional Effects of Education

I now turn to the effect of education on inequality. Consider an increase in the share of skilled workers from L_2^{1980} to L_2^{2019}. Using equation 9, it is clear that:

$$\ln\left[\frac{w_2(A^t, L^{1980})}{w_1(A^t, L^{1980})}\right] - \ln\left[\frac{w_2(A^t, L^{2019})}{w_1(A^t, L^{2019})}\right] = -\frac{1}{\sigma}\left[\ln\left(\frac{L_2^{1980}}{L_1^{1980}}\right) - \ln\left(\frac{L_2^{2019}}{L_1^{2019}}\right)\right] > 0 \tag{10}$$

The relative wage of skilled workers would be higher in 2019 if education had not improved, because their relative supply would be lower. In other words, education reduces inequality. This effect is less pronounced for higher values of σ, reflecting a lower sensitivity of relative wages to relative supplies. As

[5] In practice, accounting for imperfect substitution is equivalent to using a return to schooling that falls in-between the 2019 return $r(A^{2019}, L^{2019})$ and the return that would prevail absent educational expansion $r(A^{2019}, L^{1980})$.

shown in equation 10, this result is independent of the level of the skill bias of technology at which it is estimated: it applies to both the independent and total effects of education.

III. Data and Methodology

This section presents the methodology used to estimate the total contribution of education to global poverty reduction from 1980 to 2019. Section III.A covers data sources. Section III.B turns to the estimation of the model. Section III.C validates the methodology with new evidence from three education policies.

III.A. Data Sources

III.A.a. Survey Microdata

The starting point is a dataset of household surveys covering the joint distribution of personal income and education in 154 countries around 2019, which I have assembled for this paper. These surveys come from two main sources (see Appendix E for more details).

The first data source is the International Labor Organization's database of household surveys. Based on a considerable data collection effort and with the collaboration of statistical institutes, ILOSTAT have harmonized over 1,300 surveys, covering 130 countries over the 1990-2022 period. The database records individual-level information on wages, self-employment income, education, and other sociodemographic variables. Surveys are nationally representative and generally have large sample sizes. About two-thirds of surveys are labor force surveys designed to collect information on employment and earnings. About one-third are multi-purpose surveys that record data on both labor market variables and other dimensions of households' conditions. I keep the survey conducted closest to 2019 in each country.

The coverage of the ILO microdata is remarkable, but the information collected on education is limited in some countries. Furthermore, a number of countries are missing, including big countries such as China and Russia. To expand the coverage and quality of the database, I turn to the websites of national statistical institutes and other sources, from which I download additional household surveys for 59 countries and harmonize them in the same way as the ILO.

Table I provides descriptive statistics on the resulting database. The data cover about 10 million individuals surveyed in 154 countries. These surveys are representative of over 95% of the population of each world region. The exception is the Middle East and North Africa, where surveys either do not exist or are inaccessible to researchers (Ekhator-Mobayode and Hoogeveen, 2022). Overall, the microdata cover about 97% of the world's population and 95% of the world's GDP.[6]

III.A.b. Returns to Schooling

The second input required for the analysis is a measure of the returns to schooling. I consider two options: returns to schooling estimated by OLS with the survey data, or causally identified returns available from the existing literature.

OLS Returns In the main analysis, I rely on OLS estimates of returns to schooling by education level. The microdatabase reports information on four educational attainment categories: no schooling, incomplete or completed primary education, incomplete or completed secondary education, and incomplete or completed tertiary education. I estimate returns to schooling by level using modified Mincerian equations:

$$\ln y_i = \alpha + \beta_{pri} D_{i,pri} + \beta_{sec} D_{i,sec} + \beta_{ter} D_{i,ter} + X_i \beta + \varepsilon_i \tag{11}$$

Where y_i is total annual earned income from all jobs of individual i, $D_{i,pri}$, $D_{i,sec}$, and $D_{i,ter}$ are dummies for having reached primary, secondary, and tertiary education, and X_i is a vector of controls including gender, an age quartic, and interactions between gender and the age quartic (as in Lemieux, 2006; Autor, Goldin, and Katz, 2020).[7] I restrict the sample to individuals with positive personal income, including both wage earners and self-employed individuals. The returns to reaching each category are:

$$r_{pri}(A^{2019}, L^{2019}) = \ln\left(\frac{w_{pri}^{2019}}{w_{non}^{2019}}\right) \quad = \quad \beta_{pri} \tag{12}$$

$$r_{sec}(A^{2019}, L^{2019}) = \ln\left(\frac{w_{sec}^{2019}}{w_{pri}^{2019}}\right) \quad = \quad \beta_{sec} - \beta_{pri} \tag{13}$$

$$r_{ter}(A^{2019}, L^{2019}) = \ln\left(\frac{w_{ter}^{2019}}{w_{sec}^{2019}}\right) \quad = \quad \beta_{ter} - \beta_{sec} \tag{14}$$

Figure II plots returns to schooling by world region, converted from log points to percentage changes to ease interpretation. There are large variations across countries and education levels, in line with previous evidence covering a more limited number of countries (Psacharopoulos, 1994; Psacharopoulos and Patrinos,

[6] In nearly all countries, the survey was fielded after 2015: see Appendix Table E1.

[7] Controlling for age rather than potential experience allows comparing individuals with more education to those with less education but more work experience, which ensures that estimated returns to schooling are net of foregone experience.

2004; Banerjee and Duflo, 2005; Caselli, Ponticelli, and Rossi, 2014).[8] In almost all world regions, returns are higher at higher levels of education. In the average country, the return to having incomplete or complete primary education is 25%, the return to having incomplete or complete secondary education is 40%, and the return to having incomplete or complete tertiary education is 85%.

This suggests that returns to schooling are convex. I do not observe the distribution of years of schooling within each category, however, so it is not possible to conclude from this database. Importantly, these returns should not be interpreted as returns to completing each level. If the primary education category mostly includes incomplete degrees, for instance, r_{pri} will be lower than the return to completing primary education, while r_{sec} will partly include the effect of finishing primary school.

To shed more light on this issue, I turn to I2D2, a collection of harmonized household surveys maintained by the World Bank, which does record exact completed years of schooling for a subset of 62 countries. I investigate the convexity of returns in three ways (see Appendix F for more details).

First, I run a piecewise log-linear regression relating the log of personal income to years of schooling, with the same controls as in equation 11 and country fixed effects. Returns to schooling are strongly convex. The return per year of schooling is about 2% for the first six years of education, 8% for the next six years, and 12% above twelve years (see Table II). This pattern is visible in almost all regions.

Second, I run regressions relating the log of personal income to years of schooling and years of schooling squared.[9] In every region, the coefficient on years of schooling squared is positive and significant.

Third, I run regressions relating the log of personal income to six dummies for having reached incomplete or complete primary, secondary, or tertiary education. This specification is less straightforward to interpret, since the length of degrees varies by education level and across countries. The same pattern of convexity appears nonetheless.[10]

Together, these results provide robust evidence that returns to schooling are larger at higher levels of education. This finding contrasts with the previous macroeconomics literature (e.g., Hall and Jones, 1999), which usually assumes concave returns, and is more consistent with recent evidence (e.g., Rossi, 2022; Jedwab et al., 2023). I discuss the reasons underlying this discrepancy with previous work in Appendix F.

[8]Variations in returns are generally considered to be driven by the combination of labor supply, labor demand, and education quality differences. Rossi (2022) presents empirical evidence suggesting that education quality only plays a limited role.

[9]See Appendix Table F4. Appendix Table F3 provides results without years of schooling squared.

[10]See Appendix Table F5.

IV Returns The advantage of OLS returns is that they can be estimated for all 154 countries using a common methodology. The disadvantages are twofold. First, OLS returns may suffer from omitted variable bias, although this bias has been found to be small (Card, 1999; Gunderson and Oreopoulos, 2020). Second, our parameter of interest is the return for those newly educated since 1980, which can differ from the average return in the presence of heterogeneity (e.g., Heckman, Humphries, and Veramendi, 2018).

To make progress in tackling these issues, an alternative option is to use causally identified returns. I have assembled a new collection of instrumental variable estimates of the returns to schooling. Surveying the literature, I was able to identify 33 cases in which both OLS and IV returns were available for comparison, covering 23 countries or world regions representative of about two-thirds of the world's population.[11]

Figure III compares these OLS and IV returns. They are highly correlated ($\hat{\rho} = 0.65$). IV returns almost always exceed or are not significantly different from OLS returns, in line with previous evidence (Card, 1999). The average gap is about 40%. Strikingly, IV returns also appear to be convex. Across studies, the average returns to a year of primary, secondary, and tertiary education are 8.5%, 10%, and 12.5%.

Given the diversity of policies and specifications found across studies, it is difficult to conclude on the exact sources of variations observed in the IV-OLS gap. Nonetheless, I consider a specification in which OLS returns estimated with my data are upward corrected using OLS-IV gaps found across these studies. I then compare results using these reduced-form "IV-corrected" returns with those derived from the model.[12]

III.A.c. Educational Attainment Data

The third input required for the estimation is data on the evolution of educational attainment. The primary source is the Barro and Lee (2013) database, which records the share of individuals with no schooling, primary, secondary, and tertiary education by age and gender in 146 countries since 1950. I complement it with my own estimates for missing countries, using census data, cohort-level trends observed in the labor force surveys, and other sources (see Appendix G).

Figure IV plots the evolution of worldwide educational attainment from 1980 to 2019. There has been a rapid expansion of secondary education, from about 20% to 55% of the world's working-age population. This rise was mirrored by a large decline in the share of adults with primary education or no schooling. Tertiary education also expanded significantly, from less than 5% to over 10%.

[11] See Appendix D.1 for more details. Appendix Table D1 provides a complete list of these studies.
[12] This reduced-form specification finds support in my analysis of three natural experiments in section III.C: in each case, the aggregate effect of schooling ends up falling close to the IV return.

III.A.d. Global Income Inequality Data

The last required input is data on the income distribution in each country. I use the World Inequality Database (Blanchet et al., 2021), which reports average labor and capital income by percentile in all countries in the world from 1980 to 2019. All components of net national income are allocated to individuals, so that income distributions are consistent with macroeconomic growth rates. I construct estimates of the world distribution of income by converting all incomes to 2023 PPP US dollars using national income deflators and PPP conversion factors provided in the WID.

III.B. Methodology

I now outline the main elements of the methodology. I first present the steps followed to solve the model. I then discuss how to bring the model to the microdata.

III.B.a. Model Specification and Estimation

1) CES Production Function Until now, I worked with two skill groups for illustrative purposes, yet the data cover four. To incorporate supply effects on these groups, I introduce nests in the CES production function (following, e.g., Goldin and Katz, 2007; Fernández and Messina, 2018):

$$H^t = \left(A^t_{\overline{ter}} {L^t_{\overline{ter}}}^{\frac{\sigma_1 - 1}{\sigma_1}} + A^t_{ter} {L^t_{ter}}^{\frac{\sigma_1 - 1}{\sigma_1}} \right)^{\frac{\sigma_1}{\sigma_1 - 1}} \tag{15}$$

$$L^t_{\overline{ter}} = \left(A^t_{\overline{sec}} {L^t_{\overline{sec}}}^{\frac{\sigma_2 - 1}{\sigma_2}} + A^t_{sec} {L^t_{sec}}^{\frac{\sigma_2 - 1}{\sigma_2}} \right)^{\frac{\sigma_2}{\sigma_2 - 1}} \tag{16}$$

$$L^t_{\overline{sec}} = \left(A^t_{non} {L^t_{non}}^{\frac{\sigma_3 - 1}{\sigma_3}} + A^t_{pri} {L^t_{pri}}^{\frac{\sigma_3 - 1}{\sigma_3}} \right)^{\frac{\sigma_3}{\sigma_3 - 1}} \tag{17}$$

At the upper level, output is produced by combining tertiary-educated and non-tertiary-educated workers L^t_{ter} and $L^t_{\overline{ter}}$. The intermediate level includes workers with secondary and below-secondary education L^t_{sec} and $L^t_{\overline{sec}}$. Finally, the lower level includes workers with primary education L^t_{pri} and no schooling L^t_{non}. Technology parameters are normalized to $A^t_{\overline{ter}} = 1 - A^t_{ter}$, $A^t_{\overline{sec}} = 1 - A^t_{sec}$, and $A^t_{non} = 1 - A^t_{pri}$.

2) Elasticities of Substitution The second step is to calibrate the elasticities of substitution between skill groups. In my main specification, I use long-run elasticities, which amounts to assuming that firms would adjust their technological mix if education came back to its 1980 level. Two recent studies have made progress in estimating these elasticities. Hendricks and Schoellman (2023) show that wage gains at migration in the United States imply a long-run elasticity ranging from 5 to 8, depending on the skill cutoff chosen to estimate it (with higher cutoffs implying lower elasticities). Bils, Kaymak, and Wu (2022) estimate that current patterns of worldwide growth, returns to schooling, and cross-country technological differences imply a long-run elasticity between 4 and 6. In light of this evidence, I specify elasticities of $\sigma_1 = 4$, $\sigma_2 = 6$, and $\sigma_3 = 8$ in my benchmark specification.

3) Solving the Model Once the CES production function and elasticities are specified, it is straightforward to solve the model. The returns to schooling are:

$$\ln\left(\frac{w_{pri}^{2019}}{w_{non}^{2019}}\right) = \ln\left(\frac{A_{pri}^{2019}}{A_{non}^{2019}}\right) - \frac{1}{\sigma_3}\ln\left(\frac{L_{pri}^{2019}}{L_{non}^{2019}}\right) \tag{18}$$

$$\ln\left(\frac{w_{sec}^{2019}}{w_{pri}^{2019}}\right) = \ln\left(\frac{A_{sec}^{2019}}{A_{\overline{sec}}^{2019} A_{pri}^{2019}}\right) - \frac{1}{\sigma_2}\ln\left(\frac{L_{sec}^{2019}}{L_{\overline{sec}}^{2019}}\right) - \frac{1}{\sigma_3}\ln\left(\frac{L_{\overline{sec}}^{2019}}{L_{pri}^{2019}}\right) \tag{19}$$

$$\ln\left(\frac{w_{ter}^{2019}}{w_{sec}^{2019}}\right) = \ln\left(\frac{A_{ter}^{2019}}{A_{\overline{ter}}^{2019} A_{sec}^{2019}}\right) - \frac{1}{\sigma_1}\ln\left(\frac{L_{ter}^{2019}}{L_{\overline{ter}}^{2019}}\right) - \frac{1}{\sigma_2}\ln\left(\frac{L_{\overline{ter}}^{2019}}{L_{sec}^{2019}}\right) \tag{20}$$

These three returns have been estimated using the microdata, and the distribution of educational attainment L^{2019} is observed in the Barro-Lee database. The only unknown parameters are the technology terms A_j^{2019}, which I recover from equations 18 to 20. All parameters of the model are then known and one can directly calculate counterfactual human capital $H(A^{2019}, L^{1980})$ and wages.

4) Implied Returns to Schooling What are the returns to schooling implied by this model? In the average country, actual returns to primary, secondary, and tertiary education are about 25%, 40%, and 85%. The counterfactual returns that would prevail absent educational expansion are around 50%, 90%, and 130%.[13] The model predicts an effect of education on output that is equivalent to using returns falling in-between these two bounds. This true return, expressed per year of schooling, can be estimated as:

$$r^*_{\text{annual}}(A^{2019}) = \frac{\ln H(A^{2019}, L^{2019}) - \ln H(A^{2019}, L^{1980})}{S^{2019} - S^{1980}} \tag{21}$$

Where S^t is average years of schooling at time t. In other words, the "true" return is the constant return per year of schooling that can reproduce the decline in output predicted by the model. Actual and counterfactual

[13] See Appendix Table A1.

annualized returns can be calculated using the same principle. The actual return is 8%, the true return is 11%, and the counterfactual return is 14% in the average country. Accounting for imperfect substitution is thus equivalent to increasing the return to schooling by about 3 percentage points.

III.B.b. Distributional Growth Accounting

The next part of the methodology consists in bringing the results of the model to the microdata, which allows estimating how the income distribution would look like in each country if education had not improved. I construct these counterfactual income distributions in four steps.

1) Downgrade Education Levels The first step is to bring education back to its 1980 level in each country. I implement this "first stage" by sampling individuals and downgrading their education until reaching the counterfactual by age-gender cell (as in, e.g., Hershbein, Kearney, and Pardue, 2020).

2) Adjust Wages The second step is to adjust the earnings of the different skill groups. Consider an individual i with initial labor and mixed income $y_{iL}(A^{2019}, L^{2019})$, whose education level is shifted from s_2 to s_1. Their counterfactual income absent educational expansion is:

$$y_{iL}(A^{2019}, L^{1980}) = \exp\left[\ln\left(y_{iL}(A^{2019}, L^{2019})\right) - \ln\left(\frac{w_{s_2}(A^{2019}, L^{2019})}{w_{s_1}(A^{2019}, L^{1980})}\right)\right] \tag{22}$$

For instance, workers downgraded from tertiary to secondary education see their earnings reduced by the 2019 tertiary to counterfactual secondary wage gap. Importantly, workers whose education remains the same also see their wage change. Because of supply effects, the wage of non-treated skilled workers typically increases, while that of non-treated unskilled workers typically declines.[14]

3) Derivation of Total Income Steps 1 and 2 yield an estimate of how the distribution of labor income would look like if education had not improved. The next step is to move from labor income to total income. In my benchmark specification, I make the conservative assumption that physical capital is not affected by schooling, as in the canonical growth accounting exercise. Counterfactual income of group p then equals $y^p(A^{2019}, L^{1980}) = \exp\left(y^p(A^{2019}, L^{2019}) - (1-\alpha^p)\ln\frac{y_L^p(A^{2019}, L^{2019})}{y_L^p(A^{2019}, L^{1980})}\right)$, with α^p its capital income share.

[14]Appendix Table A8 illustrates how wages by skill group typically adjust in the average country.

4) Growth Accounting The final step is to calculate the share of growth accounted for by education for income group p, as in equation 5:

$$\text{Share}_{\text{L}}^{\text{p}} = \frac{\ln y^p(A^{2019}, L^{2019}) - \ln y^p(A^{2019}, L^{1980})}{\ln y^p(A^{2019}, L^{2019}) - \ln y^p(A^{1980}, L^{1980})} \tag{23}$$

III.C. Validation from Three Natural Experiments

The ability of this simple model to capture the effect of education may naturally be questioned. My analysis could underestimate the benefits of education if there are human capital externalities (e.g., Gennaioli et al., 2013; Chauvin et al., 2017), or overestimate them in the presence of signaling effects or negative selection (e.g., Spence, 1973; Fujimoto, Lagakos, and VanVuren, 2023). To assess the validity of my framework, I turn to causal evidence from three natural experiments (see Appendix C for more details).

III.C.a. Contexts, Data, and Methodology

I study three large-scale schooling initiatives: India's District Primary Education Program (1990s-2000s), Indonesia's INPRES school construction program (1970s), and U.S. state compulsory schooling laws (1870s-1960s). Existing work has focused on individual returns to schooling, human capital externalities, and general equilibrium effects of educational expansion (e.g., Acemoglu and Angrist, 2000; Duflo, 2001; 2004; Khanna, 2023). Less is known of the overall effects of these policies on aggregate growth and inequality.

Combining data from existing studies and additional sources, I exploit these natural experiments to estimate the causal effect of educational expansion on growth and inequality across subnational regions. I run variants of the following specification:

$$\ln y_{rt}^i = \gamma_0^i + \gamma_1^i S_{rt} + X_{rt}\beta + \delta_r + \delta_t + \varepsilon_{rt} \tag{24}$$

$$S_{rt} = \alpha_0 + \alpha_1 Z_{rt} + \eta_{rt} \tag{25}$$

Where y_{rt}^i denotes the average income of income group i in subnational region r at time t. The objective is to estimate the impact of S_{rt}, the average years of schooling of the working-age population. X_{rt} is a vector of controls, δ_r are subnational region fixed effects, and δ_t are time fixed effects. The parameters of interest are γ_1^i, providing reduced-form estimates of the macroeconomic return to schooling for different groups i.

S_{rt} is instrumented with Z_{rt}, a variable capturing quasi-experimental variation in program exposure.

In India, I rely on Khanna (2023), who estimates the impact of the DPP using a regression discontinuity design around the cutoff district literacy rate used to allocate the program. In Indonesia, I instrument district average years of schooling by the number of schools built under the INPRES program, following Duflo (2001). In the United States, the instrument is average required years of schooling across cohorts born in different states (Acemoglu and Angrist, 2000; Guo, Roys, and Seshadri, 2018). I then compare the estimated aggregate and distributional effects of each program with those predicted by the model.

III.C.b. Main Results

Figure V plots the main results, comparing estimated and simulated effects of education on average incomes by quintile. All three policies strongly reduced inequality. In India, for instance, one additional year of schooling in a treated district increases the average income of the bottom quintile in this district by 20%, compared to a null effect on that of the top 20%. Aggregate effects of education on earnings range from 8% to 15% (as shown by the dashed line in each figure), comparable to individual returns found in the same contexts (Duflo, 2001; Clay, Lingwall, and Stephens, 2021; Khanna, 2023; Li, 2024).

The model performs remarkably well. In all three cases, simulations predict higher returns to educational expansion at the bottom of the distribution. If anything, the model underestimates benefits for low-income earners in the United States. These results provide reassuring evidence that the methodology developed in this paper delivers a good approximation of the distributional effects of educational expansion, and may even provide a lower bound on benefits at the bottom of the income distribution.

IV. Education and the World Distribution of Income, 1980-2019

This section presents the main results on the total contribution of education to global economic growth and its distribution from 1980 to 2019. Section IV.A presents the key takeaways of the distributional growth accounting exercise. Section IV.B compares these findings to those of a standard growth decomposition. Section IV.C investigates the sensitivity of the results to alternative assumptions and specifications. Section IV.D explores heterogeneity across countries, cohorts, time periods, and skill groups.

IV.A. Main Results

I start by presenting the main results of the distributional growth accounting decomposition for the world as a whole in Table III. From 1980 to 2019, global average income per capita increased at an annual rate of 1.6%. The contribution of education was 0.7 points per year. Private returns to schooling therefore account for 45% of worldwide per-capita income growth over this period.

The contribution of schooling to growth varies significantly by global income group. Growth has been higher for the world's poorest 50%, but benefits from educational expansion have also been higher for this group, so that the share of growth explained by education exceeds 40%. Overall, education can account for 40% to 70% of growth for all groups within the global bottom 90%. This share is highest for the bottom 20% (58%) and middle 40% (69%), two groups that have witnessed lower growth and large gains from schooling. The contribution of education is lowest at the very top of the distribution, mainly because the bulk of top incomes consists in capital income, which by assumption is not affected by schooling.

Figure I provides a more detailed breakdown of the distribution of global economic growth from 1980 to 2019. All individuals in the world are ranked from the poorest 1% to the richest 0.01%. Annual pretax income growth is then calculated for each percentile, together with the contribution of education (lower shaded area) and residual growth from other factors (upper shaded area). Real income gains have been greatest at the middle and very top of the global income distribution, generating what has often been referred to as the "elephant curve" of global inequality and growth (Lakner and Milanovic, 2016). This pattern reflects the conjunction of trends in inequality between and within countries, including the rise of China and India (middle of the distribution), sluggish economic growth in low-income countries (bottom of the distribution), weak income gains for most households in high-income countries (upper middle of the distribution), and skyrocketing top income inequality in many parts of the world (top end of the distribution). The main contribution of this paper is to isolate gains from education, represented by the lower shaded area. These gains have been large, exceeding 1 point for most percentiles within the bottom 90%.

Another indicator that has received much attention is the share of the world's population living in extreme poverty. A difficulty is that poverty headcount ratios are based on counting individuals with incomes below a certain number rather than on actual growth rates, which makes the calculation less conceptually meaningful and more sensitive to the choice of a specific threshold. With these limitations in mind, I extend the decomposition to global poverty rates in Table IV. For this analysis, I use World Bank data, which is the most commonly used data source to measure extreme poverty. Education can account for about 35% of global poverty reduction at \$2.15 per day, 49% at \$3.65 per day, and 67% at \$6.85 per day—the three thresholds used by the World Bank to measure global poverty.[15]

[15] Appendix Table A3 reproduces this analysis using the WID. Appendix Table A2 reproduces Table III with World Bank data.

IV.B. Comparison with Standard Growth Accounting

A first way of better understanding these estimates is to study the effect of applying each of the estimation steps outlined in section III. This analysis allows comparing my results to those of a canonical growth accounting decomposition, which is useful to isolate the different channels driving the results. Table V displays the share of global average economic growth and global bottom 20% income growth explained by education with different data sources and assumptions.

1) The Standard Growth Accounting Decomposition I start by presenting results from a standard growth accounting decomposition. I follow Barro and Lee (2015), who estimate the fraction of global economic growth explained by human capital from 1960 to 2010. This decomposition only requires three ingredients: per-capita net national income data (taken from the World Inequality Database), capital income shares α (taken from the Penn World Tables to follow Barro and Lee, 2015), and an estimate of the Mincerian return to schooling (set at $r = 10\%$ per year). Human capital at time t is $H^{t,\text{standard}} = e^{rS^t}$, where S^t are average years of schooling of the working-age population. The contribution of education to growth is thus:

$$\text{Share}_L^{\text{standard}} = (1-\alpha)\frac{r \times (S^{2019} - S^{1980})}{\ln Y^{2019} - \ln Y^{1980}} \tag{26}$$

The first line of Table V presents the results. Education accounts for 33% of global average economic growth. The second column shows results for the global bottom 20%. Because this growth accounting decomposition relies on cross-country data, the poorest 20% have to be defined as the poorest 20% countries (population-weighted). Educational progress has been relatively weak in these countries. As a result, education explains about 16% of growth for the global bottom 20%.

2) Adjusting the Income Concept A first problem with this approach is that capital income shares in the Penn World Tables include most of mixed income. As a result, the implicit assumption in equation 26 is that the return to schooling only applies to a small fraction of mixed income. This does not appear to be true. OLS returns estimated in section III.A.b include all of mixed income and are, on average, indistinguishable from those estimated on wages only.[16] Aggregate effects of schooling estimated using the natural experiments studied in section III.C also include mixed income. The income concept used should thus include all of

[16] See Appendix Table F1. Let us note that this result need not imply that the capital of self-employed workers is unproductive. Rather, it suggests that education enables these workers to accumulate more capital or make this capital more productive.

mixed income, because this is the concept returns to schooling estimated in this paper apply to.

The second line of Table V presents the results when the return to schooling applies to all of mixed income. The Penn World Tables do not provide this decomposition, so I turn to the factor income shares recently estimated by Bachas et al. (2022). The contribution of education to average growth rises to 42%, and its contribution to bottom 20% growth to 25%. In the appendix, I investigate the sensitivity of my results to a more modest adjustment in which only 75% of mixed income is affected by education.[17]

3) Incorporating Within-Country Inequality In a third step, I account for within-country inequality: the global poorest 20% correspond no more to the poorest 20% countries. All other methodological ingredients stick to the standard growth accounting exercise. The average income of each income group is reduced by the same proportion within each country.

By construction, accounting for within-country inequality leaves the share of aggregate growth explained unchanged. However, it raises the contribution of education to bottom 20% growth from 25% to 36%, for two main reasons. First, the bottom 20% is now a mix of individuals from low-income and middle-income countries, some of which witnessed significant educational progress. Second, inequality has risen rapidly in many countries. This second factor increases the contribution of education simply because there is less growth among the global poor to be explained than what cross-country data suggest.

4) Incorporating Within-Country Capital Income Concentration Fourth, I account for the fact that capital income is concentrated at the top of the distribution in each country. For the majority of individuals belonging to the bottom 90%, almost all of income consists in wages or mixed income. The passthrough from schooling to income is thus close to 100% for low-income earners, rather than equal to the aggregate labor income share. As in step 3, this does not affect the share of aggregate growth explained by education. However, it raises the contribution of education to bottom 20% growth significantly, from 36% to 47%.

5) Bringing in the Microdata Fifth, I bring in the microdatabase collected for the purpose of this paper. The main difference is that returns to schooling are now allowed to vary by country and education level. The contribution of education to average growth declines, mainly because the implied average Mincerian return

[17] See Appendix Table A4. This adjustment is equivalent to using the benchmark labor shares estimated in Bachas et al. (2022), who attribute 75% of mixed income to labor as is common in the literature. The share of global economic growth explained is almost identical, highlighting that the difference between rows (1) and (2) primarily comes from differences between the PWT and Bachas et al. (2022) databases. The capital share is almost 50% in the PWT in the average country, likely reflecting a choice to attribute most of mixed income to capital, compared to 33% in Bachas et al. (2022). The share of global bottom 20% growth explained declines more due to the larger share of mixed income in total income in low- and middle-income countries.

in my data is closer to 8% than 10%. The contribution of education to global bottom 20% growth declines even more, reflecting the fact that the world's poorest individuals have mostly benefited from expansions in primary and secondary education, whose average annual returns are even lower than 8% (see Table II).

6) Accounting for Supply Effects: Distributional Component Sixth, I account for the distributional component of supply effects: education reduces inequality by increasing the relative supply of skilled workers. This step of the methodology requires data on the joint distribution of income and education, so it can only be conducted with the microdatabase.

To isolate this channel, I only adjust relative wages, leaving the average income unchanged in each country. The contribution of education to average growth is therefore the same as in the previous step. The share of growth explained by education among the world's poorest 20% increases from 32% to 46%, reflecting the large effect of education on inequality within countries.

7) Accounting for Supply Effects: Aggregate Component Finally, I account for the aggregate component of supply effects: not expanding education would have been more detrimental to growth than what returns to schooling observed in 2019 suggest. This final step affects wages differentially across countries and skill groups, generating both aggregate and distributional effects. The contribution of education to average growth rises from 31% to 45%, while the contribution of education to global bottom 20% growth increases from 46% to 58%, yielding the benchmark estimate presented at the beginning of this section.

Summary In summary, the results presented in Table V tell us two facts on education and global poverty. First, education explains almost 4 times more growth for the global poor than a standard growth accounting exercise would suggest. Changes in within-country inequality, capital income concentration, differential returns, and general equilibrium effects imply a much more complex picture than that depicted by a standard decomposition based on aggregate data. Second, accounting for the distributional effects of schooling appears essential. General equilibrium effects account for a third of the contribution of education to global poverty reduction by redistributing a large share of schooling gains from high-skilled to low-skilled workers.

IV.C. Sensitivity to Alternative Specifications

Table V highlights how assumptions regarding (1) the returns to schooling (2) supply effects, and (3) which types of income are affected by education have important implications for the analysis. I study the sensitivity of my results to alternative assumptions on these three dimensions in Table VI.

1) Returns to Schooling I first investigate the implications of using IV-corrected returns to schooling instead of model-based estimates.[18] This increases the contribution of education to average growth to 51% and its contribution to the world's poorest 20% growth to 71%.

2) Elasticities of Substitution A second important assumption relates to the degree of substitutability between skill groups. My benchmark specification assumes $\sigma_1 = 4$, $\sigma_2 = 6$, and $\sigma_3 = 8$. Table VI reports results from three alternative specifications. In the high substitutability scenario, I assume elasticities at the upper end of those found in the literature (Hendricks and Schoellman, 2023). In the low substitutability scenario, I set long-run elasticities closer to the lower bound of 4 estimated in Bils, Kaymak, and Wu (2022). In the very low substitutability scenario, I use short-run elasticities found in the literature (Katz and Murphy, 1992; Fernández and Messina, 2018; Khanna, 2023), which amounts to assuming that bringing education back to its 1980 level would lead to no endogenous adjustment in labor demand.

The share of average growth explained is moderately affected by these alternative assumptions, ranging from 41% to 62%. The share of global bottom 20% growth explained is more sensitive, ranging from 47% in the high substitutability scenario to over 100% in the very low substitutability scenario. In a world in which labor demand would not adjust, not expanding education would have led to huge increases in within-country inequality, implying no income gains for the global poor.

3) Production Function Specification I also investigate the sensitivity to using three alternative specifications of the CES production function (see Appendix D.2 for more details). The first one assumes that firms first choose between workers with below- and above-secondary education, and then choose between workers within each of these two groups. The second one is a standard CES production function with no nest and a single elasticity. The third one further accounts for imperfect substitution between age groups and returns to experience, which have been shown to be an important determinant of cross-country income differences (Lagakos et al., 2018; Rossi, 2020; Jedwab et al., 2023). As shown in Table VI, the results are essentially identical to those obtained with my benchmark functional form.

[18] This is equivalent to using IV-corrected returns instead of aggregate effects predicted by the model in step (7) of table V. I still assume that distributional effects of education are the same as in the benchmark specification. See Appendix D.1 for more details.

4) Physical Capital Adjustment My main results assume that education has no effect on physical capital per person. This assumption is conservative: one should expect physical capital to endogenously respond to educational expansion. More specifically, equation 4 can be rearranged as:

$$1 = \frac{\alpha}{1-\alpha}\frac{\Delta \ln(K/Y)}{\Delta \ln Y} + \frac{\Delta \ln(z)}{\Delta \ln Y} + \frac{\Delta \ln(H)}{\Delta \ln Y} \tag{27}$$

As is standard in the literature (e.g., Hsieh and Klenow, 2010). In this specification, capital per person is allowed to change in response to human capital accumulation, consistent with a long-run growth model in which human capital and TFP do not affect the capital-output ratio in steady state. The passthrough from education to output is then 1 instead of $1-\alpha$. In this scenario, education explains 62% of global economic growth and 67% among the world's poorest 20%.[19]

6) Other Robustness Checks Finally, I conduct four additional robustness checks.

A first robustness check focuses on educational attainment categories. In my main specification, I assume that workers are homogeneous within each of the four skill groups. One may be concerned that the distribution of human capital within these categories (e.g., incomplete versus complete secondary education) may have changed over time. I study this possibility in Appendix D.3, focusing on 37 countries with sufficiently high-quality data. The results are insensitive to this additional layer of detail.

A second concern relates to who benefits from schooling. In the main specification, I randomly sample individuals and downgrade their education until matching 1980 levels. I investigate the implications of accounting for heterogeneous educational expansion by age, gender, subnational region (India), and race (South Africa, United States) in Appendix D.4. Using more refined categories has limited effects.

A third robustness check centers on school attendance: if education had not improved, more adolescents and young adults would be working today instead of being in school. I derive an upper bound on this opportunity cost of schooling in Appendix D.5. The main results are barely affected.[20]

A last concern relates to education quality. If education quality has changed, then educational attainment in 1980 and 2019 might not be comparable. I investigate this concern at length in Appendix D.6. Although data are scarce, available evidence suggests stagnating quality in most countries (Altinok, Angrist, and

[19] Appendix Table D3 presents the full distributional growth accounting decomposition by income group with this specification.

[20] Another related margin through which education could affect poverty is fertility. Empirical evidence is mixed. Female education has been found to reduce early pregnancy (Osili and Long, 2008; Duflo, Dupas, and Kremer, 2015; Ozier, 2018), but not necessarily lifetime fertility (Duflo et al., 2024). The implications for my results are thus unclear. If anything, accounting for negative effects of education on dependency ratios would likely magnify the pro-poor nature of educational expansion.

Patrinos, 2018; Angrist et al., 2021; Le Nestour, Moscoviz, and Sandefur, 2022). Even under conservative assumptions on a potential decline in quality, my main results are unaffected.

IV.D. Heterogeneity

I conclude this section with a discussion on heterogeneity, decomposing the worldwide effects of education between and within countries, by world region, and by time period.

1) Growth Accounting Within and Between Countries I first decompose the effect of education on inequality between and within countries.[21] From 1980 to 2019, global inequality remained constant. Absent educational progress, it would have risen by 20%, primarily because education reduces within-country inequality—the effect of schooling on between-country inequality has been close to zero. Education has thus sufficiently mitigated the rise of within-country inequality to keep overall global inequality stable.

2) Growth Accounting by World Region A second way of better understanding the results is to decompose them by world region. In the average country, education explains about 25% of aggregate growth. This figure is highest in Europe and Northern America, Latin America, and Sub-Saharan Africa, and lowest in China and India. In all regions, education explains over 30% of growth among the poorest 50%.[22]

3) Growth Accounting by Time Period Finally, the results can also be decomposed by time period. The share of growth explained by schooling has been lower in recent years, mainly due to the exceptional catchup of China and India, but it has remained high for the global poor. Education accounts for about 20% of aggregate growth since 2000, but 40% among the world's poorest 20%.[23]

V. The Role of Skill-Biased Technical Change

The previous section focused on the total contribution of education, that is, the effect of education given skill-biased technical change. In this section, I turn to isolating the role played by skill-biased technical change in making education valuable in 109 countries from 2000 to 2019. Section V.A presents the data and methodology. Sections V.B and V.C provide estimates of skill-biased technical change and the independent

[21] See Appendix Table A5, which reports a Theil decomposition of global inequality from 1980 to 2019.
[22] See Appendix Table A6. I also provide complete growth decompositions by world region in Appendix Table D4.
[23] See Appendix Table A7.

contribution of education to growth. Section V.D proposes a tentative analysis of the contribution of skill-biased technical change to worldwide growth and poverty reduction.

V.A. Historical Survey Microdata

Quantifying the independent contribution of education to growth for the world as a whole over 1980-2019 would require surveys fielded in 1980 in each country. Such surveys do not exist. However, I was able to find surveys fielded around 2000 in a subsample of countries (see Appendix E for more details).

Data Sources The main data source is the I2D2 database, a repository of household surveys maintained by the World Bank. The coverage of labor force surveys is lower than in the ILO microdatabase, which is why I do not use it as my primary source in the main analysis. Its historical coverage is much greater, however, which makes it better suited for estimating the independent effect of education since 2000.

I searched for all surveys fielded in the late 1990s or early 2000s with detailed information on personal income and educational attainment. Such surveys are available for 71 countries in I2D2. I complement them with other surveys from country-specific sources and other data portals. The resulting microdatabase covers 109 countries located in all regions and representative of about 80% of the world's population.

The quality of these surveys is highly variable and generally lower than the ones used in the rest of the paper. They have lower sample size and are typically not labor force surveys. Sub-Saharan Africa is strongly underrepresented. Furthermore, the distribution of educational attainment is less consistent with the Barro-Lee database. For these reasons, I view the analysis presented in this section as more suggestive.

Methodology The methodology is the same as in the rest of the paper, except that the quantity of interest is $H(A^{2000}, L^{2019}) - H(A^{2000}, L^{2000})$. I start by solving the model, exactly as in section III.B. First, I estimate the returns to schooling in 2000, $r_j(A^{2000}, L^{2000})$, using the historical survey microdatabase. Second, I use these returns to recover the technology parameters A_j^{2000}. All parameters of the model are then known and one can directly calculate the independent contribution of education to growth. The independent effect of education on inequality is the same as its total effect, as highlighted in equation 10, so it is straightforward to estimate distributional effects of education in each country.

V.B. *Skill-Biased Technical Change Since 2000*

I start by presenting two sets of estimates of skill-biased technical change, depending on whether one assumes short-run or long-run elasticities.[24] Using long-run elasticities should imply rates of exogenous technological change that are close to zero on average, since it is equivalent to assuming that changes in demand for skilled labor result from educational expansion (see section II.B). In other words, results with short-run elasticities should be interpreted as reflecting actual skill-biased technical change, while results with long-run elasticities correspond to residual skill-biased technical change when one assumes that changes in labor demand reflect endogenous responses to educational expansion.

Table VII presents results on skill-biased technical change by world region over 2000-2019, defined as annualized changes in relative demand for primary-educated workers A_{pri}/A_{non}, secondary-educated workers $A_{sec}/A_{\overline{sec}}$, and tertiary-educated workers $A_{ter}/A_{\overline{ter}}$. Focusing on short-run elasticities, demand for primary-educated workers is found to have declined, demand for secondary-educated workers to have stagnated, and demand for tertiary-educated workers to have slightly increased in the average country. There is considerable heterogeneity across world regions. Demand for skilled workers has declined in Sub-Saharan Africa, India, and especially China, mirroring the large drop in the return to college recently documented by Hanushek, Wang, and Zhang (2023). Skill-biased technical change has also been limited in Latin America, confirming previous evidence (Fernández and Messina, 2018). Europe and Northern America, where demand for college-educated workers has increased rapidly, stand out as the exception.

The results are similar with long-run elasticities, except that the exogenous component of skill-biased technical change is found to have been zero or negative in most regions. In other words, almost all of skill-biased technical change is interpreted as having resulted from educational expansion if one uses long-run elasticities. This should not come as a surprise, given that long-run elasticities are precisely calibrated to rationalize variations in skilled labor supply and wage premia without invoking technical change.

V.C. *The Contribution of Education to Growth With and Without Skill-Biased Technical Change*

I now turn to studying the role played by skill-biased technical change in amplifying the benefits of schooling. Table VIII compares the independent (without skill-biased technical change) and total (with skill-biased technical change) shares of aggregate growth explained by education by world region. As discussed in section IV.D, the total contribution of education is lower over 2000-2019 than 1980-2019,

[24] Appendix Table A9 reports the corresponding returns to schooling by level and world region in 2000 and 2019.

mainly because of the catchup of China and India. In the average country, it reaches 20-25%.

Skill-biased technical change has significantly amplified the effect of education (columns 1 to 3). In the average country, the independent contribution of schooling is about 70% of its total effect: 30% of the benefits of education have been made possible by growing demand for skilled labor. There are large variations across regions. In Europe and Northern America, the interaction between education and technology amounts to more than half of the total contribution of education. In China and India, this interaction is negative: education would have had larger effects if labor demand had remained constant.

With long-run elasticities, the gap between the independent and total contributions of education is much smaller—about zero in the average country and below 15% in all regions but Europe and Northern America. In other words, exogenous skill-biased technical change is found to have played almost no role if one assumes that labor demand reflects an endogenous response of firms to educational expansion.

V.D. Skill-Biased Technical Change and the World Distribution of Income Since 2000

I conclude this paper with a tentative extension of this analysis to the world distribution of income. I restrict the sample to the 109 countries with available data in both 2000 and 2019. I then construct measures of the independent and total contributions of education to growth for different global income groups, assuming that these 109 countries are representative of the world.

Table IX presents the results for short-run and long-run elasticities specifications. As discussed previously, using lower elasticities implies that the total effect of education is greater, especially among the global poor, but also that a larger fraction of this effect results from an interaction between education and technology.

With short-run elasticities, the total contribution of education to worldwide growth reaches 25%, about 30% of which was made possible by skill-biased technical change. This figure is much larger at the middle and top ends of the world distribution of income, reflecting the rapid rise in demand for skilled labor in high-income countries. For the global poor, in contrast, technological change has only played a modest role. Education accounts for 66% of growth among the world's poorest 20%, and would still have accounted for 63% of growth absent skill-biased technical change, reflecting the low or negative growth in skilled labor demand in China, India, and Sub-Saharan Africa documented in Table VII. The results are similar with long-run elasticities, except that the total contribution of education is estimated to have been smaller (30-35% for the world's poorest 20%) and labor demand dynamics to have played a smaller role.

VI. Conclusion

This article quantified the role played by education in the historical reduction of global poverty. Combining macroeconomic growth decomposition with the canonical model of education and the wage structure, I proposed a "distributional growth accounting" framework identifying the contribution of education to growth within and across countries. Under conservative assumptions, education can explain a large fraction of income gains among the world's poorest individuals, in the order of 60-70% and potentially more. This finding puts public education policies at the center of the remarkable reduction of global poverty observed in the past decades.

The focus of this article was on the poverty-reducing effects of education from an accounting perspective, yet much remains to be understood of the drivers of educational expansion itself. On the one hand, one should expect schooling decisions to respond to the economic environment, whether it is rising demand for skilled labor or other factors (e.g., Foster and Rosenzweig, 1996; Restuccia and Vandenbroucke, 2013). On the other hand, there are many examples of significant and long-lasting disconnections between the two: for instance, growth in the supply of skilled workers has stalled in the United States despite rapid skill-biased technical change (Autor, Goldin, and Katz, 2020), while the exact opposite has happened in Latin America (Fernández and Messina, 2018). Many other factors could also explain educational progress, with public policies being a natural candidate (Bharti and Yang, 2024; Gethin, 2024). Identifying the respective roles of technological progress, behavioral responses, and institutions in driving education and its effects on long-run growth remains an important avenue for future research.

More generally, the results presented in this article illustrate how combining cross-country microdata with simple conceptual frameworks can help uncover new insights on the long-run drivers of the world distribution of income that would otherwise be missed by more aggregate analyses. Similar methods could be developed to study other key transformations of the past decades, such as trade globalization, structural change, financial integration, and international migration. The microeconomics literature provides ample and growing empirical evidence on the economic effects of these factors in specific contexts. Combined with new microdata similar to those used in this paper, complementary data sources, and adequate theoretical frameworks, this evidence could be aggregated to shed light on the role played by these long-run processes in the reduction of global poverty and inequality.

DEVELOPMENT RESEARCH GROUP, THE WORLD BANK

References

Acemoglu, Daron and Joshua Angrist (2000). "How Large Are Human-Capital Externalities? Evidence from Compulsory Schooling Laws". In: *NBER Macroeconomics Annual* 15.1, pp. 9–59.

Ahmed, Amer, Maurizio Bussolo, Marcio Cruz, Delfin S. Go, and Israel Osorio-Rodarte (2020). "Global Inequality in a more educated world". In: *Journal of Economic Inequality* 18 (1), 585–616.

Altinok, Nadir, Noam Angrist, and Harry A. Patrinos (2018). "Global Data Set on Education Quality (1965-2015)". World Bank Policy Research Working Paper No. 8314.

Angrist, Noam, Simeon Djankov, Pinelopi K. Goldberg, and Harry A. Patrinos (2021). "Measuring human capital using global learning data". In: *Nature* 592.1, pp. 403–408.

Atkin, David (2016). "Endogenous Skill Acquisition and Export Manufacturing in Mexico". In: *American Economic Review* 106.8, 2046–2085.

Autor, David, Claudia Goldin, and Lawrence F. Katz (2020). "Extending the Race between Education and Technology". In: *AEA Papers and Proceedings* 110.1, pp. 347–351.

Bachas, Pierre, Matthew H. Fisher-Post, Anders Jensen, and Gabriel Zucman (2022). "Globalization and Factor Income Taxation". NBER Working Paper 29819.

Banerjee, Abhijit and Esther Duflo (2005). "Growth Theory through the Lens of Development Economics". In: pp. 473–552.

Barro, Robert J. and Jong-Wha Lee (2013). "A new data set of educational attainment in the world, 1950–2010". In: *Journal of Development Economics* 104.1, pp. 184–198.

— (2015). *Education Matters: Global Schoolig Gains from the 19th Century to the 21st Century*. Oxford University Press.

Bharti, Nitin and Li Yang (2024). "The Making of China and India in the 21st Century: Long-Run Human Capital Accumulation from 1900 to 2020". World Inequality Lab Working Paper.

Bils, Mark, Baris Kaymak, and Kai-Jie Wu (2022). "Labor Substitutability Among Schooling Groups". NBER Working Paper.

Blanchet, Thomas, Lucas Chancel, Ignacio Flores, and Marc Morgan (2021). *Distributional National Accounts Guidelines: Methods and Concepts Used in the World Inequality Database*. Tech. rep.

Buera, Francisco J., Joseph P. Kaboski, and Robert M. Townsend (2023). "From Micro to Macro Development". In: *Journal of Economic Literature* 61.2, pp. 471–503.

Card, David (1999). "The Causal Effect of Education on Earnings". In: *Handbook of Labor Economics*. Ed. by Orley C. Ashenfelter and David Card. Elsevier, pp. 1801–1863.

— (2001). "Estimating the Return to Schooling: Progress on Some Persistent Econometric Problems". In: *Econometrica* 69.5, pp. 1127–1160.

Caselli, Francesco and Antonio Ciccone (2019). "The Human Capital Stock: A Generalized Approach: Comment". In: *American Economic Review* 109.3, pp. 1155–1174.

Caselli, Francesco and Wilbur John II Coleman (2006). "The World Technology Frontier". In: *American Economic Review* 96.3, pp. 499–522.

Caselli, Francesco, Jacopo Ponticelli, and Federico Rossi (2014). "A New Dataset on Mincerian Returns". Working Paper.

Chancel, Lucas and Thomas Piketty (2021). “Global Income Inequality, 1820–2020: the Persistence and Mutation of Extreme Inequality”. In: *Journal of the European Economic Association* 19.6, 3025–3062.

Chauvin, Juan Pablo, Edward Glaeser, Yueran Ma, and Kristina Tobio (2017). “What is different about urbanization in rich and poor countries? Cities in Brazil, China, India and the United States”. In: *Journal of Urban Economics* 98.1, pp. 17–49.

Chen, Shaohua and Martin Ravallion (2010). “The Developing World Is Poorer Than We Thought, But No Less Successful In the Fight Against Poverty”. In: *Quarterly Journal of Economics* 125.4, pp. 1577–1625.

Clay, Karen, Jeff Lingwall, and Melvin Jr. Stephens (2021). “Laws, educational outcomes, and returns to schooling evidence from the first wave of U.S. state compulsory attendance laws”. In: *Labour Economics* 68.1, pp. 1019–1035.

Collin, Matthew and David Weil (2020). “The Effect of Increasing Human Capital Investment on Economic Growth and Poverty: A Simulation Exercise”. In: *Journal of Human Capital* 14.1, pp. 43–83.

Deming, David J. (2022). “Four Facts about Human Capital”. In: *Journal of Economic Perspectives* 36.3, pp. 75–102.

Duflo, Esther (2001). “Schooling and Labor Market Consequences of School Construction in Indonesia: Evidence from an Unusual Policy Experiment”. In: *American Economic Review* 91.4, pp. 795–813.

— (2004). “The medium run effects of educational expansion: evidence from a large school construction program in Indonesia”. In: *Journal of Development Economics* 74.1, pp. 163–197.

Duflo, Esther, Pascaline Dupas, and Michael Kremer (2015). “Education, HIV, and Early Fertility: Experimental Evidence from Kenya”. In: *American Economic Review* 105 (9), 2757–2797.

Duflo, Esther, Pascaline Dupas, Elizabeth Spelke, and Mark Walsh (2024). “Intergenerational Impacts of Secondary Education: Experimental Evidence from Ghana”. NBER Working Paper.

Edmonds, Eric V., Nina Pavcnik, and Petia Topalova (2010). “Trade Adjustment and Human Capital Investments: Evidence from Indian Tariff Reform”. In: *American Economic Journal: Applied Economics* 2.4, pp. 42–75.

Ekhator-Mobayode, Uche E. and Johannes Hoogeveen (2022). “Microdata collection and openness in the Middle East and North Africa”. In: *Data and Policy* 4.31, pp. 1–17.

Fernández, Manuel and Julián Messina (2018). “Skill premium, labor supply, and changes in the structure of wages in Latin America”. In: *Journal of Development Economics* 135.1, pp. 555–573.

Fisher-Post, Matthew and Amory Gethin (2023). “Government Redistribution and Development: Global Estimates of Tax-and-Transfer Progressivity, 1980-2019”. Working Paper.

Foster, Andrew D. and Mark R. Rosenzweig (1996). “Technical Change and Human-Capital Returns and Investments: Evidence from the Green Revolution”. In: *American Economic Review* 86.4, pp. 931–953.

Fujimoto, Junichi, David Lagakos, and Mitchell VanVuren (2023). “Macroeconomic Effects of Free Secondary Schooling in the Developing World”. NBER Working Paper Series.

Gennaioli, Nicola, Rafael La Porta, Florencio Lopez-de Silanes, and Andrei Shleifer (2013). “Human Capital and Regional Development”. In: *The Quarterly Journal of Economics* 128.1, 105–164.

Gethin, Amory (2024). “Revisiting Global Poverty Reduction: Public Goods and the World Distribution of Income, 1980-2022”. Working Paper.

Goldin, Claudia and Lawrence F. Katz (2007). “The Race between Education and Technology: The Evolution of U.S. Educational Wage Differentials, 1890 to 2005”. NBER Working Paper.

— (2008). *The Race Between Education and Technology*. Harvard University Press.

Gunderson, Morley and Philip Oreopoulos (2020). “Returns to education in developed countries”. In: *The Economics of Education*. Ed. by Steve Bradley and Colin Green. Academic Press, pp. 39–51.

Guo, Junjie, Nicolas Roys, and Ananth Seshadri (2018). “Estimating Aggregate Human Capital Externalities”. Working Paper.

Hall, Robert E. and Charles I. Jones (1999). “Why Do Some Countries Produce So Much More Output Per Worker Than Others?” In: *The Quarterly Journal of Economics* 114.1, pp. 83–116.

Hammar, Olle and Daniel Waldenström (2020). “Global Earnings Inequality, 1970-2018”. In: *The Economic Journal* 130.632, pp. 2526–2545.

Hanushek, Eric A., Yuan Wang, and Lei Zhang (2023). “Understanding Trends in Chinese Skill Premiums, 2007-2018”. NBER Working Paper.

Heckman, James J., John Eric Humphries, and Gregory Veramendi (2018). “Returns to Education: The Causal Effects of Education on Earnings, Health, and Smoking”. In: *Journal of Political Economy* 126.1, pp. 197–246.

Hendricks, Lutz and Todd Schoellman (2018). “Human Capital and Development Accounting: New Evidence from Wage Gains at Migration”. In: *The Quarterly Journal of Economics* 133.2, 665–700.

— (2023). “Skilled Labor Productivity and Cross-Country Income Differences”. In: *American Economic Journal: Macroeconomics* 15.1, pp. 240–268.

Hershbein, Brad, Melissa S. Kearney, and Luke W. Pardue (2020). “College Attainment, Income Inequality, and Economic Security: A Simulation Exercise”. In: *AEA Papers and Proceedings* 110.1, pp. 352–355.

Hsiao, Allan (2023). “Educational Investment in Spatial Equilibrium: Evidence from Indonesia”. Working Paper.

Hsieh, Chang-Tai and Peter J. Klenow (2010). “Development Accounting”. In: *American Economic Journal: Macroeconomics* 2.1, pp. 207–223.

Jedwab, Remi, Paul Romer, Asif M. Islam, and Roberto Samaniego (2023). “Human Capital Accumulation at Work: Estimates for the World and Implications for Development”. In: *American Economic Journal: Macroeconomics* 15.3, pp. 191–223.

Jones, Benjamin F. (2014). “The Human Capital Stock: A Generalized Approach”. In: *American Economic Review* 104.11, 3752–3777.

Katz, Lawrence F. and Kevin M. Murphy (1992). “Changes in Relative Wages, 1963-1987: Supply and Demand Factors”. In: *The Quarterly Journal of Economics* 107.1, pp. 35–78.

Khanna, Gaurav (2023). “Large-Scale Education Reform in General Equilibrium: Regression Discontinuity Evidence from India”. In: *Journal of Political Economy* 131.2, pp. 549–591.

Lagakos, David, Benjamin Moll, Tommaso Porzio, Nancy Qian, and Todd Schoellman (2018). “Life Cycle Wage Growth across Countries”. In: *Journal of Political Economy* 126.2, pp. 797–849.

Lakner, Christoph and Branko Milanovic (2016). “Global Income Distribution: From the Fall of the Berlin Wall to the Great Recession”. In: *The World Bank Economic Review* 30.2, pp. 203–232.

Le Nestour, Alexis, Laura Moscoviz, and Justin Sandefur (2022). “The Long-Run Decline of Education Quality in the Developing World”. Working Paper.

Lemieux, Thomas (2006). “The "Mincer Equation" Thirty Years After Schooling, Experience, and Earnings”. In: *Jacob Mincer. A Pioneer of Modern Labor Economics*. Ed. by Shoshana Grossbard. Springer. Chap. 11, 127–145.

Li, Sophie (2024). “Returns to Education for Women in the Mid-Twentieth Century: Evidence from Compulsory Schooling Laws”. Working Paper.

Mankiw, Gregory N., David Romer, and David N. Weil (1992). “A Contribution to the Empirics of Economic Growth”. In: *Quarterly Journal of Economics* 107.2, pp. 407–437.

Moretti, Enrico (2004). “Estimating the social return to higher education: evidence from longitudinal and repeated cross-sectional data”. In: *Journal of Econometrics* 121, pp. 175–212.

Murphy, Kevin M. and Robert H. Topel (2016). “Human Capital Investment, Inequality, and Economic Growth”. In: *Journal of Labor Economics* 34.2, pp. 99–127.

Osili, Una Okonkwo and Bridget Terry Long (2008). “Does Female Schooling Reduce Fertility? Evidence from Nigeria”. In: *Journal of Development Economics* 87 (1), pp. 57–75.

Ozier, Owen (2018). “The Impact of Secondary Schooling in Kenya: A Regression Discontinuity Analysis”. In: *Journal of Human Resources* 53 (1), pp. 157–188.

Pinkovskiy, Maxim and Xavier Sala-i-Martin (2016). “Lights, Camera ... Income! Illuminating the National Accounts-Household Surveys Debate”. In: *The Quarterly Journal of Economics* 131.2, pp. 579–631.

Porzio, Tommaso, Federico Rossi, and Gabriella Santangelo (2022). “The Human Side of Structural Transformation”. In: *American Economic Review* 112.8, pp. 2774–2814.

Psacharopoulos, George (1994). “Returns to Investment in Education: A Global Update”. In: *World Development* 22.9, pp. 1325–1343.

Psacharopoulos, George and Harry Anthony Patrinos (2004). “Returns to Investment in Education: A Further Update”. In: *Education Economics* 12.2, pp. 111–134.

Queiró, Francisco (2022). “Entrepreneurial Human Capital and Firm Dynamics”. In: *The Review of Economic Studies* 89.4, 2061–2100.

Restuccia, Diego and Guillaume Vandenbroucke (2013). “The Evolution of Education: A Macroeconomic Analysis”. In: *International Economic Review* 54 (3), pp. 915–936.

Rossi, Federico (2020). “Human Capital and Macroeconomic Development: A Review of the Evidence”. In: *The World Bank Research Observer* 35.2, pp. 227–262.

— (2022). “The Relative Efficiency of Skilled Labor across Countries: Measurement and Interpretation”. In: *American Economic Review* 112.1, pp. 235–266.

Sala-i-Martin, Xavier (2006). “The World Distribution of Income: Falling Poverty and... Convergence, Period”. In: *The Quarterly Journal of Economics* 121.2, pp. 351–397.

Solow, Robert M. (1957). “Technical Change and the Aggregate Production Function”. In: *Review of Economics and Statistics* 39.1, pp. 312–320.

Spence, Michael (1973). “Job Market Signaling”. In: *Quarterly Journal of Economics* 87 (3), pp. 355–374.

United Nations (2023). *The Sustainable Development Goals Report*. United Nations.

Vu, Khoa and Tu-Anh Vu-Thanh (2022). “Higher Education Expansion, Labor Market, and Firm Productivity in Vietnam”. Working Paper.

Table I – A New Survey Microdatabase on Education and Inequality

	Countries	Observations	Share of Population Covered
Europe	39	785,036	100%
Northern America	2	539,862	100%
Latin America	25	4,139,887	98.2%
Asia-Pacific	30	2,773,236	97.9%
Middle East and North Africa	15	936,170	81.0%
Sub-Saharan Africa	43	892,362	99.0%
World	154	10,066,553	97.2%

Notes. The table reports the number of countries covered by the survey microdata, the total number of observations, and the share of the total population covered by world region and in the world as a whole. See Online Appendix E for more details.

Table II – Returns Per Year of Schooling by Level and World Region

	(1) All Countries	(2) Latin America	(3) China	(4) India	(5) Other Asia	(6) MENA	(7) Sub-Saharan Africa
Years of Schooling: 0-6	0.018***	0.071***	0.064***	0.018***	0.014***	0.017***	0.067***
	(0.001)	(0.002)	(0.010)	(0.002)	(0.002)	(0.002)	(0.004)
Years of Schooling: 7-12	0.079***	0.090***	0.086***	0.057***	0.072***	0.010***	0.055***
	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
Years of Schooling: 13+	0.123***	0.111***	0.109***	0.161***	0.085***	0.042***	0.170***
	(0.001)	(0.001)	(0.004)	(0.003)	(0.001)	(0.001)	(0.003)
N	1,291,371	781,614	30,036	122,870	119,659	78,910	158,282
R Squared	0.79	0.88	0.21	0.39	0.91	0.74	0.78

Notes. The table reports results of pooled piecewise regressions relating the log of personal income to years of schooling, with knots at 6 and 12 years of education. In India, the return to a year of education is about 2% for the first six years, 6% for the next six years, and 16% above twelve years. All estimates include country fixed effects and control for gender, an age quartic, and interactions between gender and the age quartic. The full sample covers 62 countries with detailed educational attainment information. Observations are weighted to match the total population of each country. See Online Appendix F.2 for more details on the data sources and empirical specification.

Table III – Distributional Growth Accounting, World, 1980-2019

	Annual Income Growth (%)	Contribution of Education (pp.)	Share of Growth Explained (%)
Full Population	1.6%	0.7	45%
Bottom 50%	2.4%	1.1	43%
Bottom 20%	1.9%	1.1	58%
Next 30%	2.6%	1.0	41%
Middle 40%	1.5%	1.1	69%
Top 10%	1.6%	0.5	30%
Top 1%	2.0%	0.2	9.9%
Top 0.1%	2.5%	0.07	2.9%

Notes. The table reports actual real annual income growth rates, the contribution of education to growth, and the corresponding share of growth explained by education for different groups of the world distribution of income. The average income of the world's poorest 20% grew by 1.9% per year from 1980 to 2019, 58% of which can be accounted for by education. See Online Appendix B for additional methodological details.

Table IV – Education and Global Poverty Reduction, 1980-2019

	1980	2019	Difference (%)	Share of Decline Explained (%)
Global Poverty: $2.15/Day				
Actual	47%	14%	-71%	
Counterfactual	47%	26%	-46%	35%
Global Poverty: $3.65/Day				
Actual	61%	28%	-54%	
Counterfactual	61%	44%	-28%	49%
Global Poverty: $6.85/Day				
Actual	70%	49%	-30%	
Counterfactual	70%	63%	-10%	67%

Notes. The table compares the actual evolution of the global poverty headcount ratio to the evolution it would have followed absent educational expansion. Global poverty at $2.15 per day declined by 71% from 1980 to 2019. Absent educational expansion, it would have declined by 46%. Education thus accounts for 35% of global poverty reduction during this period. All global poverty headcount ratios calculated using 2017 PPP USD. The income concept is per-capita pretax income, estimated by combining disposable income and consumption distributions from the World Bank data portal with estimates of the distribution of direct taxes and government transfers from Gethin (2024) and Fisher-Post and Gethin (2023). See Appendix Table A3 for comparable results using pretax income distributions from the World Inequality Database. Online Appendix B provides additional methodological details.

Table V – From Standard to Distributional Growth Accounting

		Share of Growth Explained, 1980-2019	
		Global Average	Global Bottom 20%
	Standard Growth Accounting		
(1)	Cross-Country Data, 10% Return	33%	16%
(2)	+ Adjusted Income Concept	42%	25%
(3)	+ Within-Country Inequality	42%	36%
(4)	+ Heterogeneous Labor Shares	42%	47%
(5)	+ Microdata	31%	32%
(6)	+ Supply Effects: Distributional Component	31%	46%
(7)	+ Supply Effects: Aggregate Component	45%	58%

Notes. The table reports the share of global economic growth and growth among the world's poorest 20% explained by education depending on methodological assumptions and data sources used. Standard growth accounting: only rely on cross-country data, assuming a uniform 10% return to schooling and that education only affects a fraction of mixed income in each country. Adjusted income concept: account for the fact that education affects all of mixed income. Within-country inequality: account for within-country inequality—the world's poorest 20% do not all live in the poorest 20% countries. Heterogeneous labor shares: account for the fact that labor income is concentrated at the bottom of the distribution in each country. Microdata: bring in the microdata, allowing returns to schooling to vary by country and education level. Supply effects, distributional component: account for the distributional implications of supply effects—absent educational expansion, the relative wage of skilled workers would be higher. Supply effects, aggregate component: account for the aggregate implications of supply effects—absent educational expansion, the return to schooling would be higher. See Online Appendix B for additional details on each methodological step. Online Appendices E to G provide additional information on the underlying data sources.

Table VI – Sensitivity to Alternative Specifications

	Share of Growth Explained, 1980-2019	
	World Average	Global Bottom 20%
Benchmark Specification	45%	58%
IV Returns to Schooling	51%	71%
Alternative Degrees of Substitutability		
High Substitutability: $\sigma_1 = 5, \sigma_2 = 8, \sigma_3 = \infty$	41%	47%
Low Substitutability: $\sigma_1 = 2, \sigma_2 = 4, \sigma_3 = 6$	53%	78%
Very Low Substitutability: $\sigma_1 = 1.5, \sigma_2 = 2.5, \sigma_3 = 4$	62%	109%
Alternative Production Functions		
CES With Alternative Nesting Structure	44%	55%
CES With No Nest	43%	57%
CES With Imperfect Substitution Between Age Groups	44%	57%
Physical Capital Affected by Education	62%	67%

Notes. The table reports how results on the share of growth explained by education vary depending on assumptions regarding the returns to schooling, the degree of substitutability between skill groups, functional forms, and whether physical capital is affected by education. See Online Appendix D for additional details on each specification.

Table VII – Annual Rates of Skill-Biased Technical Change by World Region, 2000-2019

	Assuming Short-Run Elasticities			Assuming Long-Run Elasticities		
	Primary A_{pri}/A_{non}	Secondary $A_{sec}/A_{\overline{sec}}$	Tertiary $A_{ter}/A_{\overline{ter}}$	Primary A_{pri}/A_{non}	Secondary $A_{sec}/A_{\overline{sec}}$	Tertiary $A_{ter}/A_{\overline{ter}}$
Average Country	-0.7%	-0.1%	+0.8%	-1.1%	-1.2%	-0.4%
Europe / Northern America		+1.5%	+1.9%		+0.6%	+0.9%
Latin America	-0.6%	+1.0%	+0.7%	-0.7%	-0.4%	-0.4%
China	-1.0%	-0.6%	-1.7%	-1.6%	-2.2%	-2.6%
India	-0.9%	-2.1%	+1.0%	-1.2%	-2.9%	-0.5%
Other Asia-Pacific	-0.4%	+1.1%	+2.5%	-0.8%	-0.1%	+0.8%
Middle East and North Africa	-0.1%	+1.3%	+1.3%	-0.4%	+0.2%	+0.1%
Sub-Saharan Africa	-0.9%	+0.5%	-0.0%	-1.1%	-0.3%	-0.2%

Notes. The table reports annualized rates of skill-biased technical change by world region and in the average country, that is, $\frac{1}{19}(\ln \frac{A_j^{2019}}{A_i^{2019}} - \ln \frac{A_j^{2000}}{A_i^{2000}})$ for pairs of skill groups j and i in each country. Subscripts non, pri, $\overline{sec}$, sec, $\overline{ter}$, and ter refer to workers with no schooling, primary, below secondary, secondary, below tertiary, and tertiary education, respectively. Short-run elasticities: $\sigma_1 = 1.5, \sigma_2 = 2.5, \sigma_3 = 4$. Long-run elasticities: $\sigma_1 = 4, \sigma_2 = 6, \sigma_3 = 8$. Population-weighted averages of technology terms estimated in each country. The table covers 109 countries with data on incomes and education around 2000 and 2019. Estimates are reported for countries with sample sizes sufficiently large to estimate changes in relative demand for primary (47 countries), secondary (83 countries), and tertiary education (107 countries). See Online Appendices B and E for additional details on estimation methods and data sources.

Table VIII – Share of Growth Explained by Education by World Region
With and Without Skill-Biased Technical Change, 2000-2019

	Assuming Short-Run Elasticities			Assuming Long-Run Elasticities		
	(1) Without Skill-Biased Technical Change	(2) With Skill-Biased Technical Change	(3) Without / With (1) / (2)	(4) Without Skill-Biased Technical Change	(5) With Skill-Biased Technical Change	(6) Without / With (4) / (5)
Average Country	18%	25%	72%	22%	21%	102%
Europe / Northern America	16%	36%	44%	23%	33%	72%
Latin America	53%	64%	82%	59%	57%	103%
China	9%	8%	115%	10%	7%	152%
India	18%	15%	122%	20%	12%	161%
Other Asia-Pacific	14%	29%	48%	20%	22%	88%
Middle East and North Africa	9%	15%	60%	11%	11%	102%
Sub-Saharan Africa	17%	23%	75%	21%	21%	99%

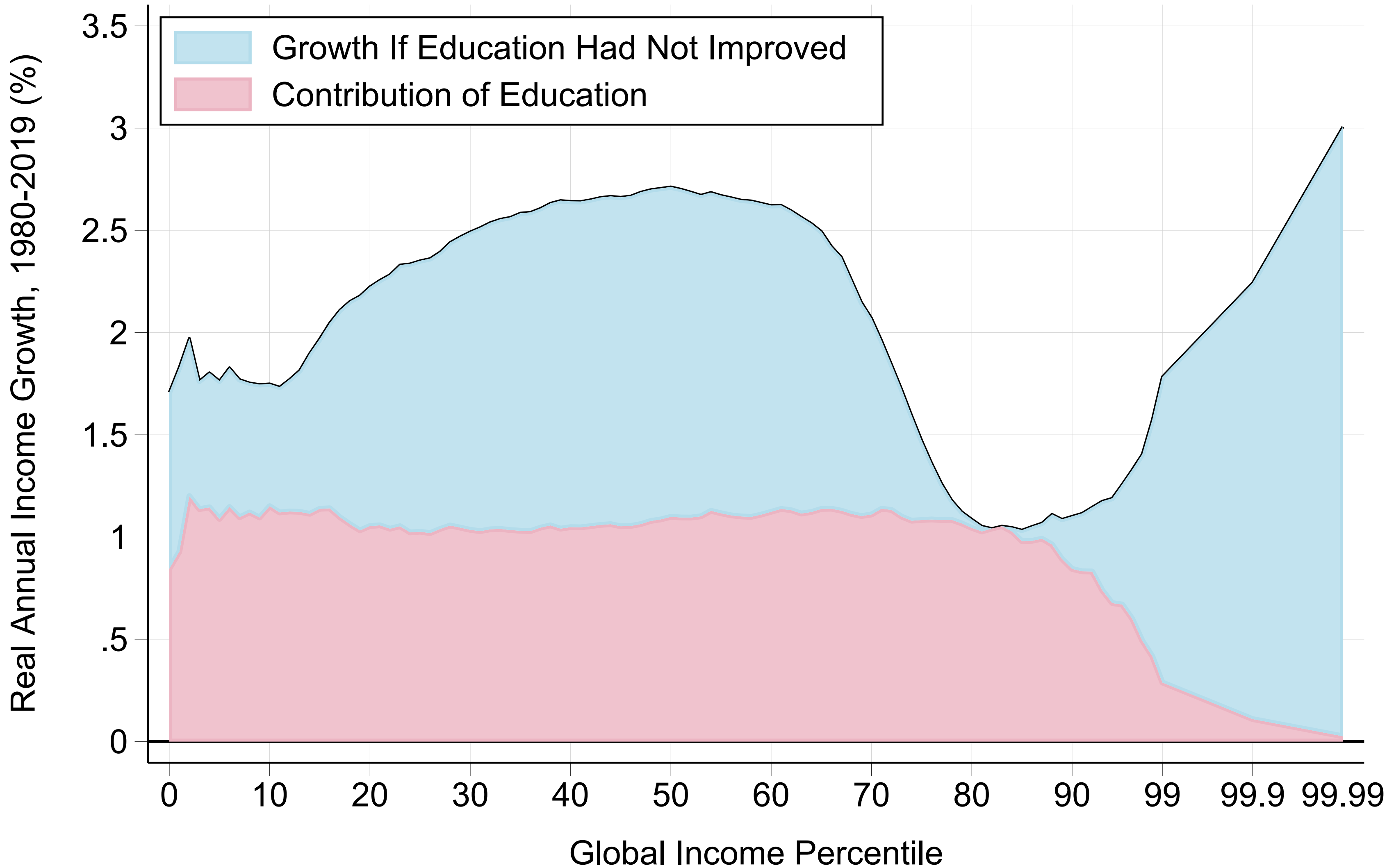
Notes. The table compares the independent and total shares of growth explained by education in the average country and by world region. Columns 1 and 4 report the "independent" effect that education would have had on growth absent skill-biased technical change. Columns 2 and 5 report the "total" effect that education had on growth given skill-biased technical change. Short-run elasticities: $\sigma_1 = 1.5, \sigma_2 = 2.5, \sigma_3 = 4$. Long-run elasticities: $\sigma_1 = 4, \sigma_2 = 6, \sigma_3 = 8$. Population-weighted averages of shares of growth explained in each country. The table covers 109 countries with data on incomes and education around 2000. See Online Appendices B and E for additional details on estimation methods and data sources.

Table IX – Share of Worldwide Growth Explained by Education by Income Group
With and Without Skill-Biased Technical Change, 2000-2019

	Assuming Short-Run Elasticities			Assuming Long-Run Elasticities		
	(1) Without Skill-Biased Technical Change	(2) With Skill-Biased Technical Change	(3) Without / With (1) / (2)	(4) Without Skill-Biased Technical Change	(5) With Skill-Biased Technical Change	(6) Without / With (4) / (5)
Full Population	17%	25%	68%	21%	21%	98%
Bottom 50%	48%	51%	95%	36%	32%	114%
Bottom 20%	63%	66%	95%	44%	39%	112%
Next 30%	46%	48%	94%	35%	30%	115%
Middle 40%	22%	27%	82%	23%	21%	109%
Top 10%	1.5%	15%	10%	13%	18%	74%

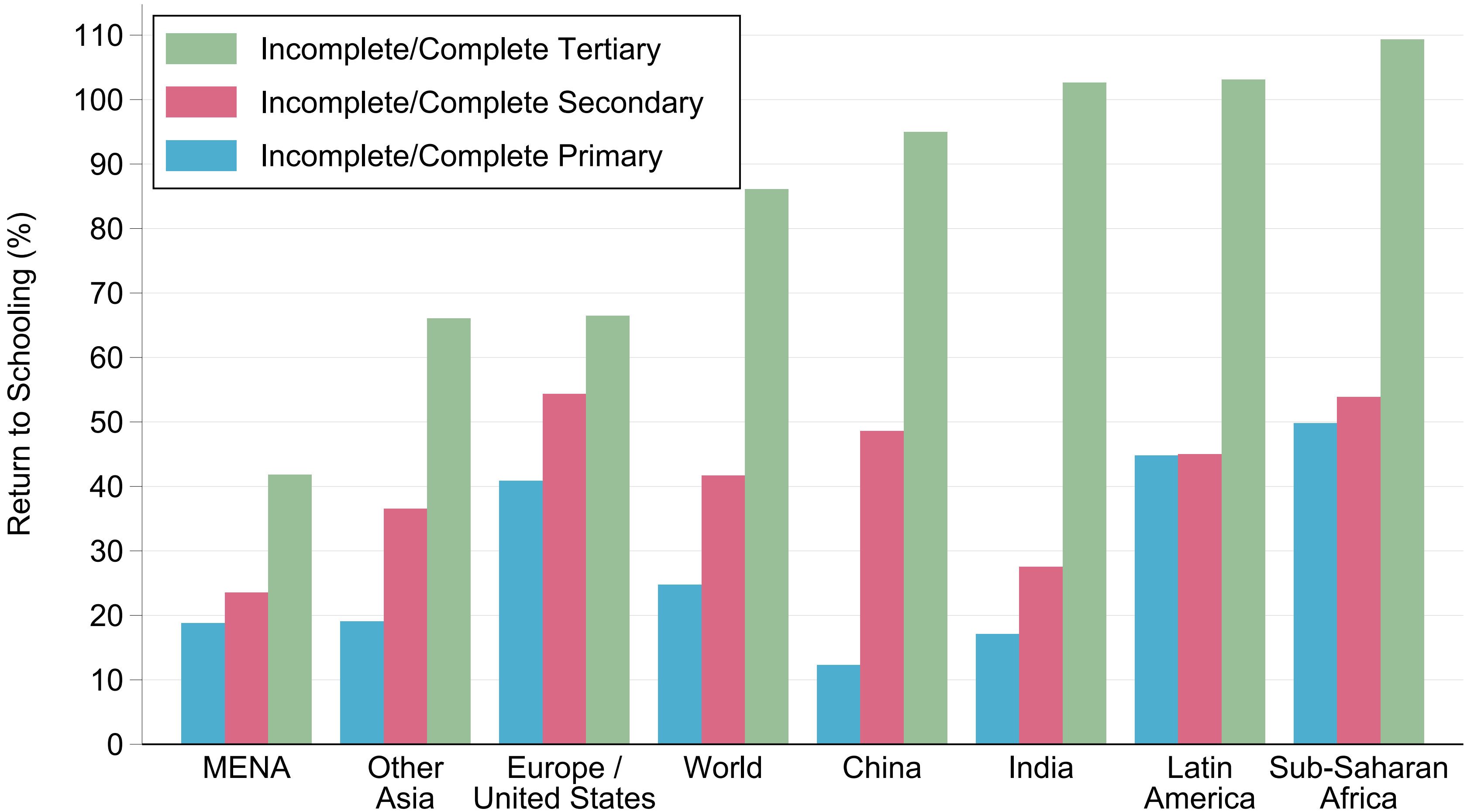
Notes. The table compares the independent and total shares of growth explained by education for different groups of the world distribution of income. Columns 1 and 4 report the "independent" effect that education would have had on growth absent skill-biased technical change. Columns 2 and 5 report the "total" effect that education had on growth given skill-biased technical change. Short-run elasticities: $\sigma_1 = 1.5, \sigma_2 = 2.5, \sigma_3 = 4$. Long-run elasticities: $\sigma_1 = 4, \sigma_2 = 6, \sigma_3 = 8$. The estimation is based on data for 109 countries with information on incomes and education around 2000, which together are representative of about 80% of the world's population. See Online Appendices B and E for additional details on estimation methods and data sources.

Figure I – Education and the Distribution of Global Economic Growth, 1980-2019



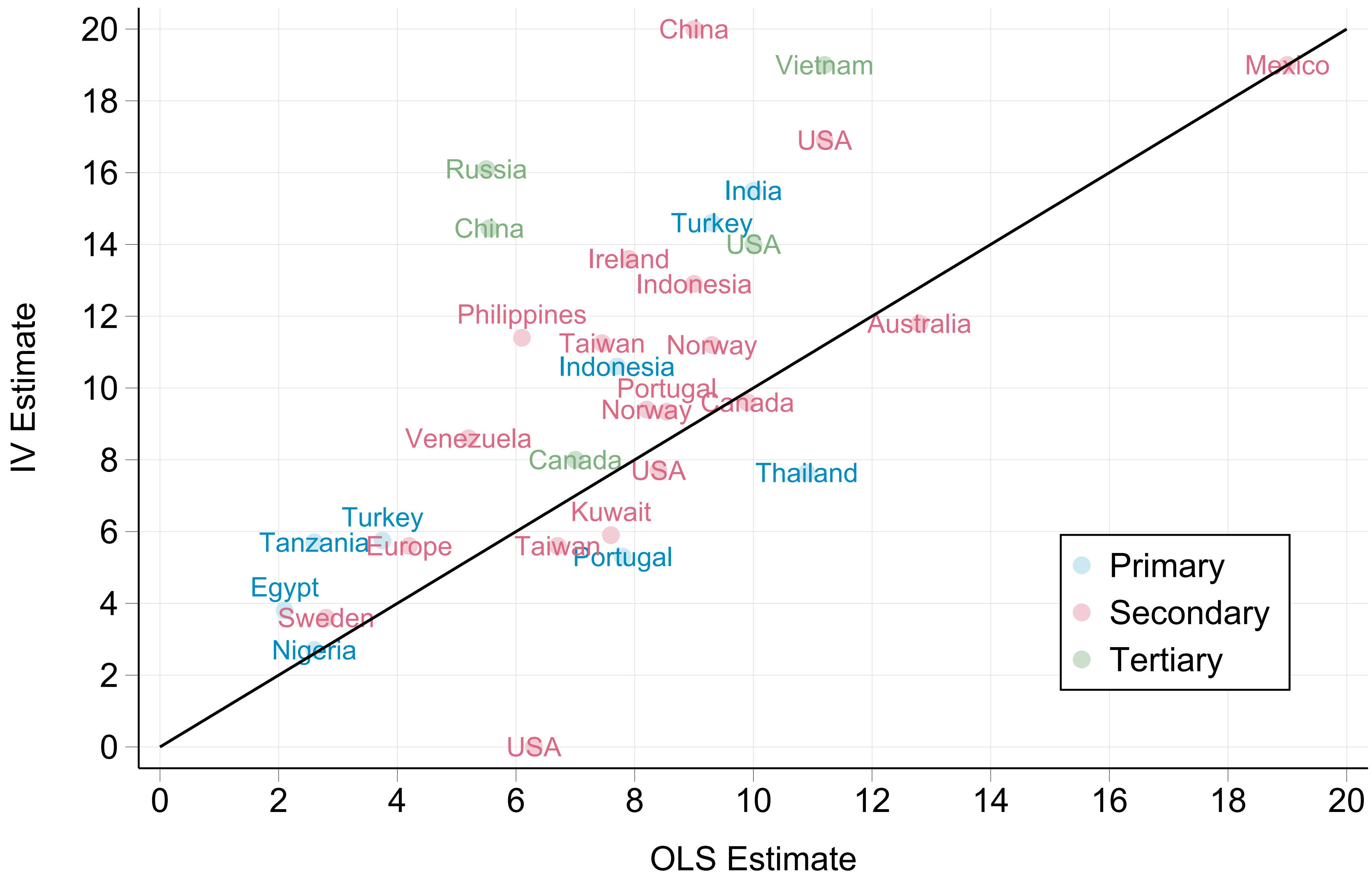
Notes. The figure plots total real income growth by global income percentile from 1980 to 2019, decomposing it into a part that can be explained by education and an unexplained component. The upper shaded area represents the growth rates that would have prevailed absent any improvement in educational attainment of the world's working-age population during this period. The lower shaded area represents the corresponding contribution of education to economic growth. From 1980 to 2019, the average income of the 20th percentile of the world distribution of income grew by 2.2% per year, 1 percentage point of which can be explained by education. Education thus accounts for about 45% of growth among this group. See Online Appendix B for additional methodological details.

Figure II – Total Returns to Schooling by World Region



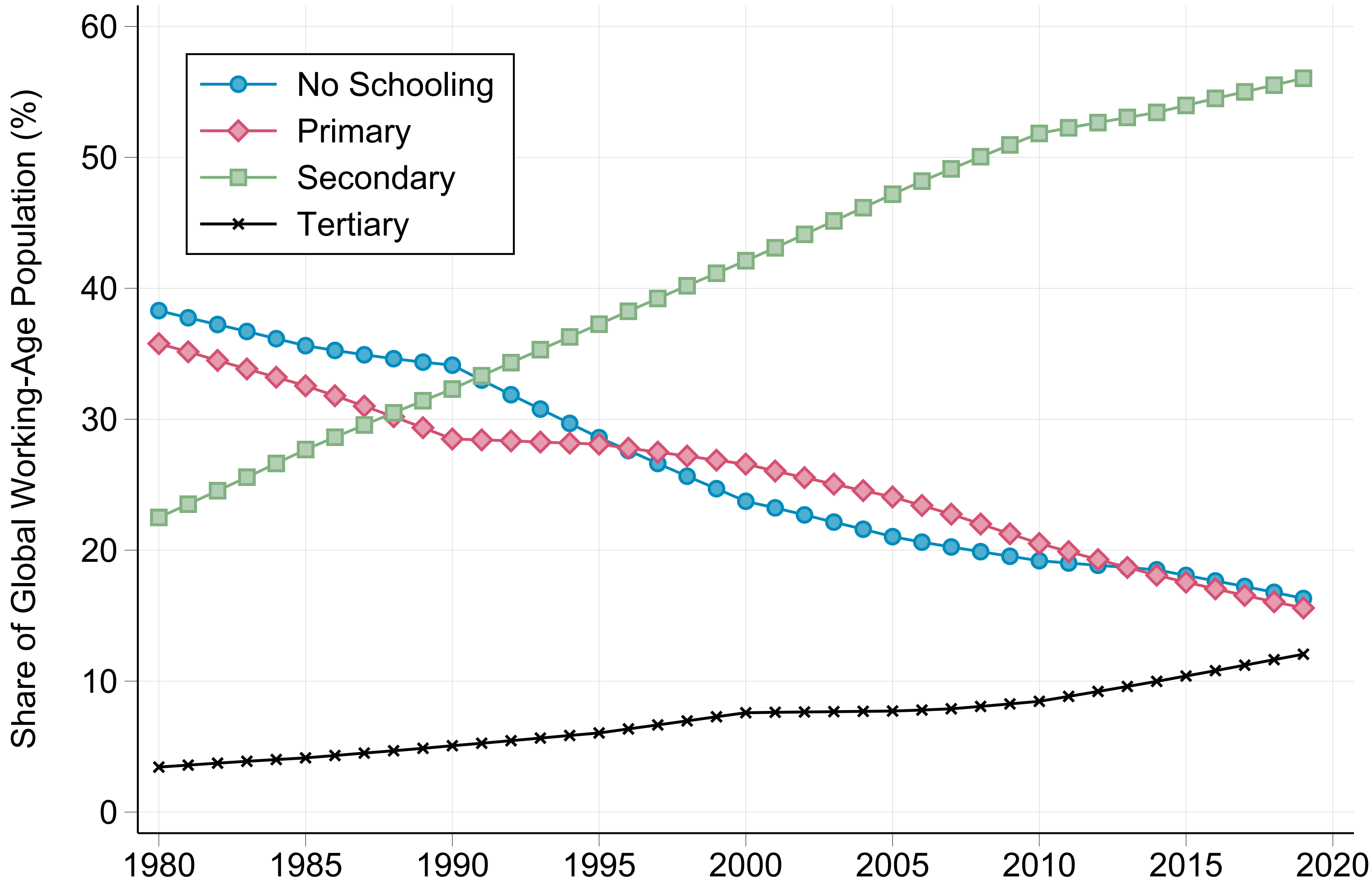
Notes. The figure plots returns to schooling by education level and world region. Interpretation: in the average Sub-Saharan African country, having incomplete or complete primary education increases earnings by 50%, incomplete or complete secondary education further increases earnings by an additional 55%, and incomplete or complete tertiary education further increases earnings by an additional 110%. The return to education level j in a given country is $R_j = 100 \times \left(\exp\left(r_j(A^{2019}, L^{2019}) \right) - 1 \right)$, where $r_j(A^{2019}, L^{2019})$ is estimated in each country using equations 11 to 14. Population-weighted averages of returns estimated in each country. See Online Appendix F.1 for additional methodological details.

Figure III – Returns to Schooling: OLS versus IV Estimates



Notes. The figure compares ordinary least squares (x-axis) and instrumental variable (y-axis) estimates of the return to an additional year of schooling. OLS estimates generally correspond to coefficients obtained from a Mincerian equation of the log of earnings on years of schooling, estimated over the entire working-age population. In contrast, IV estimates rely on quasi-experimental variation in access to a specific level of education (primary, secondary, or tertiary). Author's elaboration compiling estimates from existing empirical studies: see Appendix Table D1.

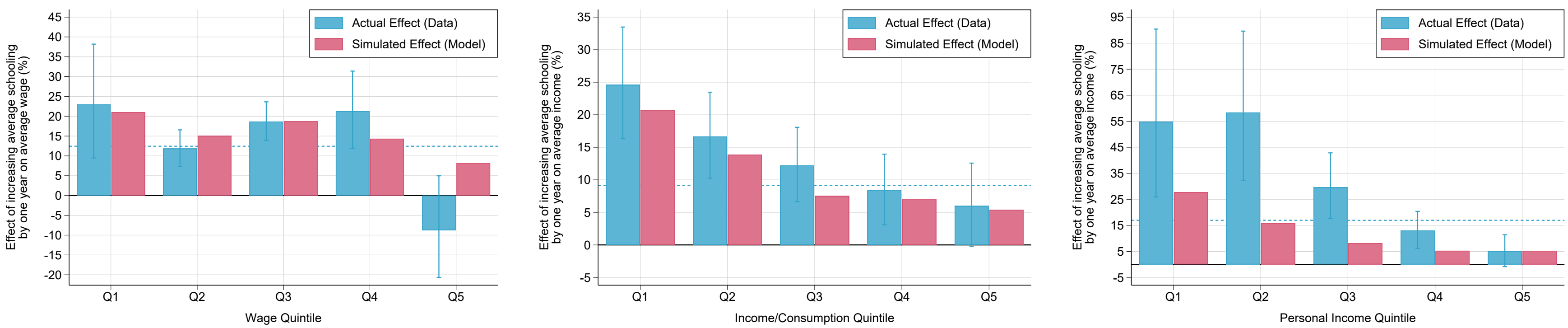
Figure IV – Educational Attainment of the World's Working-Age Population, 1980-2019



Notes. The figure plots the distribution of educational attainment of the working-age population in the world as a whole. From 1980 to 2019, the share of the world's working-age population having reached secondary education grew from about 20% to 55%. Author's calculations combining data from the Barro-Lee database and other sources (see Online Appendix G for more details).

Figure V – Validation: Actual Versus Simulated Distributional Effects of Education Expansion Policies in India, Indonesia, and the United States

(a) India (b) Indonesia (c) United States



Notes. The three figures compare actual causal effects of educational expansion on the average income of each quintile with simulated effects predicted by the model. Capped spikes correspond to 95% confidence intervals. The dashed line shows the estimated effect of average regional years of schooling on the average income. India: effect of increasing average district schooling by one year on individual wages, instrumenting schooling with exposure to the District Primary Education Program. Estimates combine NES microdata with exposure to the policy from Khanna (2023). Indonesia: effect of increasing average district schooling by one year on per-adult consumption, instrumenting schooling with exposure to the INPRES program. Estimates combine SUSENAS 1993-2019 microdata with INPRES program intensity from Duflo (2001). United States: effect of increasing average state schooling by one year on personal income, instrumenting schooling with state compulsory schooling laws. Estimates combine 1940-2000 census microdata with compulsory schooling laws from Acemoglu and Angrist (2000) and Clay, Lingwall, and Stephens (2021). Simulated effects: the return to schooling is set to 16% in India, 11% in Indonesia, and 12% in the United States, following estimates of the individual returns to schooling found in existing studies; the elasticity of substitution is set to 6 in all three cases. See Online Appendix C for more details.

DISTRIBUTIONAL GROWTH ACCOUNTING: EDUCATION AND THE REDUCTION OF GLOBAL POVERTY, 1980-2019

AMORY GETHIN

July 7, 2025

SUPPLEMENTARY ONLINE APPENDIX

Abstract

This appendix supplements my article "Distributional Growth Accounting: Education and the Reduction of Global Poverty, 1980-2019." It contains additional methodological details, as well as supplementary figures and tables.

Contents

A. Additional Key Figures and Tables

Table A1 – Actual, Counterfactual, and True Returns to Schooling by World Region

	Primary		Secondary		Tertiary		Implied Return Per Year of Schooling		
	2019 Return	Counterfactual Return	2019 Return	Counterfactual Return	2019 Return	Counterfactual Return	2019 Return	True Return	Counterfactual Return
World Average	25%	48%	42%	89%	86%	134%	7.8%	11.0%	13.9%
Europe / Northern America	41%	51%	54%	127%	66%	122%	9.3%	13.0%	15.5%
Latin America	45%	61%	45%	108%	103%	114%	7.1%	9.4%	11.3%
China	12%	39%	49%	117%	95%	143%	8.3%	12.8%	15.9%
India	17%	32%	27%	53%	103%	166%	8.0%	10.8%	14.0%
Other Asia-Pacific	19%	47%	37%	67%	66%	123%	6.1%	8.7%	11.4%
Middle East and North Africa	19%	48%	24%	61%	42%	71%	4.4%	6.9%	10.2%
Sub-Saharan Africa	50%	81%	54%	96%	109%	149%	9.6%	12.3%	16.0%

Notes. The table reports actual, counterfactual, and true returns to schooling by world region and education level. Columns 2 to 7 report returns observed in 2019, $r_j(A^{2019}, L^{2019})$, versus counterfactual returns that would prevail absent educational expansion, $r_j(A^{2019}, L^{1980})$. The last three columns report the implied returns per year of schooling, calculated as $r^*_{\text{annual}}(A^{2019}) = 100 \times \frac{\ln H(A^{2019}, L^{2019}) - \ln H(A^{2019}, L^{1980})}{S^{2019} - S^{1980}}$ with S average years of schooling of the working-age population as reported in the Barro-Lee database. In other words, the 2019 implied return is the return per year that can reproduce the decline in output observed when using 2019 returns by level to construct the counterfactual. The implied true return per year of schooling, $r^*_{\text{annual}}(A^{2019})$, is the return that can reproduce the decline in output predicted by the model. All figures are population-weighted averages of returns estimated in each country.

Table A2 – Distributional Growth Accounting, World, 1980-2019: World Bank Data

	Annual Income Growth (%)	Contribution of Education (pp.)	Share of Growth Explained (%)
Full Population	1.4%	0.9	67%
Bottom 50%	2.7%	1.2	43%
Bottom 20%	2.5%	1.2	47%
Next 30%	2.8%	1.2	43%
Middle 40%	1.4%	1.2	82%
Top 10%	1.2%	0.7	62%
Top 1%	1.6%	0.6	35%
Top 0.1%	2.1%	0.5	23%

Notes. The table reports actual real annual income growth rates, the contribution of education to growth, and the corresponding share of growth explained by education for different groups of the world distribution of income. The income concept is per-capita pretax income, estimated by combining disposable income and consumption distributions from the World Bank data portal with estimates of the distribution of direct taxes and government transfers from Gethin (2024) and Fisher-Post and Gethin (2023).

Table A3 – Education and Global Poverty Reduction, 1980-2019: WID Data

	1980	2019	Difference (%)	Share of Decline Explained (%)
Global Poverty: $2.15 / Day				
Actual	21%	9%	-58%	
Counterfactual	21%	14%	-36%	39%
Global Poverty: $3.65 / Day				
Actual	42%	15%	-65%	
Counterfactual	42%	23%	-46%	30%
Global Poverty: $6.85 / Day				
Actual	58%	29%	-50%	
Counterfactual	58%	42%	-28%	44%

Notes. The table compares the actual evolution of the global poverty headcount ratio to the evolution it would have followed absent educational expansion since 1980. All global poverty headcount ratios calculated using 2017 PPP USD. The income concept is pretax national income, as reported in the World Inequality Database. See Table IV for comparable results using per-capita consumption distributions from the World Bank.

Table A4 – From Standard to Distributional Growth Accounting
(Not All of Mixed Income Affected by Education)

		Share of Growth Explained, 1980-2019	
		Global Average	Global Bottom 20%
(1)	Standard Growth Accounting Cross-Country Data, 10% Return	33%	16%
(2)	+ Adjusted Income Concept	41%	22%
(3)	+ Within-Country Inequality	41%	33%
(4)	+ Heterogeneous Labor Shares	41%	45%
(5)	+ Microdata	30%	25%
(6)	+ Supply Effects: Distributional Component	30%	38%
(7)	+ Supply Effects: Aggregate Component	42%	46%

Notes. This table reproduces Table V but assumes that only 75% of mixed income is affected by education in rows 2 to 7. This amounts to using the benchmark labor shares estimated in Bachas et al. (2022), which attribute 75% of mixed income to labor income, instead of labor shares including all of mixed income as in Table V.

Table A5 – Education and Inequality Between and Within Countries, 1980-2019

	1980	2019	Difference
Theil Index of Global Inequality			
Actual	1.09	1.09	0.00
Counterfactual	1.09	1.32	0.22
Between-Country Component			
Actual	0.63	0.36	-0.27
Counterfactual	0.63	0.37	-0.26
Within-Country Component			
Actual	0.46	0.73	0.27
Counterfactual	0.46	0.95	0.48
Within-Country Share (%)			
Actual	42%	67%	25
Counterfactual	42%	72%	30

Notes. The table compares the actual evolution of global inequality since 1980 to the evolution it would have followed absent educational expansion, decomposing these transformations into a between-country component and a within-country component. Within-country share: share of global inequality explained by inequality within countries.

Table A6 – Distributional Growth Accounting by World Region and Country Income Group, 1980-2019

	Full Population			Bottom 50%		
	Annual Income Growth (%)	Contribution of Education (pp.)	Share of Growth Explained (%)	Annual Income Growth (%)	Contribution of Education (pp.)	Share of Growth Explained (%)
Average Country	2.9%	0.7	24%	2.4%	1.2	49%
Europe / Northern America	1.5%	0.8	50%	0.9%	1.4	>100%
Latin America	0.6%	0.8	>100%	0.9%	1.4	>100%
China	6.1%	0.8	14%	4.6%	1.5	32%
India	4.0%	0.6	16%	2.8%	0.9	34%
Other Asia-Pacific	2.8%	0.7	25%	2.7%	1.1	39%
Middle East and North Africa	1.5%	0.5	31%	1.7%	0.8	45%
Sub-Saharan Africa	1.0%	0.8	74%	1.3%	1.0	77%
Low-income	0.9%	0.8	89%	1.3%	1.0	78%
Low-middle-income	3.0%	0.6	19%	2.5%	0.9	35%
High-middle-income	3.9%	0.8	21%	3.2%	1.4	44%
High-income	1.7%	0.7	45%	1.0%	1.4	>100%

Notes. The table reports actual real income growth rates, the contribution of education, and the corresponding share of growth that can be explained by education, for the full population and the poorest 50%. Population-weighted averages of country-specific growth rates and contributions of education by world region, by country income group, and in the world as a whole (average country).

Table A7 – Distributional Growth Accounting, World, 2000-2019

	Annual Income Growth (%)	Contribution of Education (pp.)	Share of Growth Explained (%)
Full Population	2.1%	0.5	22%
Bottom 50%	3.1%	1.0	33%
Bottom 20%	2.8%	1.1	42%
Next 30%	3.2%	1.0	31%
Middle 40%	2.9%	0.7	23%
Top 10%	1.5%	0.3	18%
Top 1%	1.9%	0.09	5.0%
Top 0.1%	2.2%	0.01	0.4%

Notes. The table reports actual real annual income growth rates, the contribution of education to growth, and the corresponding share of growth explained by education for different groups of the world distribution of income over the 2000-2019 period.

Table A8 – Distributional Growth Accounting by Skill Group, 1980-2019: Actual Minus Counterfactual Income by Skill Group, Average Country (%)

		Actual Minus Counterfactual Income (%)	
	Share of Workers (%)	Without Imperfect Substitution	With Imperfect Substitution
Always No Schooling	12.1%	0%	-22.1%
Newly No Schooling	21.3%	-34.5%	-49.2%
Always Primary	6.4%	0%	-16.5%
Newly Primary	27.9%	-34.9%	-45.3%
Always Secondary	11.5%	0%	6.5%
Newly Secondary	12.8%	-39.5%	-33.4%
Always Tertiary	7.4%	0%	30.7%
Average Income		-23.9%	-29.8%

Notes. The table reports how much lower or higher the wages of different skill groups would be in the average country (population-weighted) if education had not improved: $\frac{w_j(A^{2019},L^{1980})-w_j(A^{2019},L^{2019})}{w_j(A^{2019},L^{2019})}$. Gains or losses from educational expansion are reported separately for the newly unskilled (who see their education decline in the counterfactual) and the always skilled or unskilled (who do not see their education change in the counterfactual). Without imperfect substitution: results without supply effects. With imperfect substitution: incorporate supply effects.

Table A9 – Returns to Schooling by World Region, 2000-2019

	Primary		Secondary		Tertiary	
	2000	2019	2000	2019	2000	2019
Average Country	59%	20%	89%	40%	94%	84%
Europe / Northern America			59%	53%	61%	64%
Latin America	67%	43%	78%	44%	115%	98%
China	67%	12%	146%	49%	174%	95%
India	56%	17%	119%	27%	85%	103%
Other Asia-Pacific	50%	19%	54%	38%	62%	69%
Middle East and North Africa	35%	19%	26%	18%	48%	38%
Sub-Saharan Africa	72%	35%	68%	54%	95%	95%

Notes. The table reports estimates of the returns to schooling $r_j(A^t, L^t)$ by world region and in the average country in 2000 and 2019, re-expressed as percentage differences to ease interpretation. Population-weighted averages of returns to schooling estimated in each country. The table covers 109 countries with data on incomes and education around both 2000 and 2019.

B. Additional Methodological Details

This section presents the steps followed to solve the model and estimate the total contribution of education to growth by income group in each country.

B.1. Solving the Model

I start by solving the model. The production function is:

$$
\begin{aligned}
L &= \left(A_{\overline{ter}} L_{\overline{ter}}^{\frac{\sigma_1-1}{\sigma_1}} + A_{ter} L_{ter}^{\frac{\sigma_1-1}{\sigma_1}}\right)^{\frac{\sigma_1}{\sigma_1-1}} && \text{(B1)}\\
L_{\overline{ter}} &= \left(A_{\overline{sec}} L_{\overline{sec}}^{\frac{\sigma_2-1}{\sigma_2}} + A_{sec} L_{sec}^{\frac{\sigma_2-1}{\sigma_2}}\right)^{\frac{\sigma_2}{\sigma_2-1}} && \text{(B2)}\\
L_{\overline{sec}} &= \left(A_{non} L_{non}^{\frac{\sigma_3-1}{\sigma_3}} + A_{pri} L_{pri}^{\frac{\sigma_3-1}{\sigma_3}}\right)^{\frac{\sigma_3}{\sigma_3-1}} && \text{(B3)}
\end{aligned}
$$

Where country and time subscripts are omitted to simplify the exposition. At the upper level, output is produced by combining tertiary-educated and non-tertiary-educated workers L_{ter} and $L_{\overline{ter}}$. The intermediate level includes workers with secondary L_{sec} and below-secondary education $L_{\overline{sec}}$. Finally, the lower level includes workers with primary education L_{pri} and no schooling L_{non}.

Wages Profit maximization implies the following wages:

$$
\begin{aligned}
W_{\overline{ter}} &= L^{\frac{1}{\sigma_1}} A_{\overline{ter}} L_{\overline{ter}}^{-\frac{1}{\sigma_1}} && \text{(B4)}\\
W_{ter} &= L^{\frac{1}{\sigma_1}} A_{ter} L_{ter}^{-\frac{1}{\sigma_1}} && \text{(B5)}\\
W_{\overline{sec}} &= L^{\frac{1}{\sigma_1}} A_{\overline{ter}} L_{\overline{ter}}^{-\frac{1}{\sigma_1}} L_{\overline{ter}}^{\frac{1}{\sigma_2}} A_{\overline{sec}} L_{\overline{sec}}^{-\frac{1}{\sigma_2}} && \text{(B6)}\\
W_{sec} &= L^{\frac{1}{\sigma_1}} A_{\overline{ter}} L_{\overline{ter}}^{-\frac{1}{\sigma_1}} L_{\overline{ter}}^{\frac{1}{\sigma_2}} A_{sec} L_{sec}^{-\frac{1}{\sigma_2}} && \text{(B7)}\\
W_{non} &= L^{\frac{1}{\sigma_1}} A_{\overline{ter}} L_{\overline{ter}}^{-\frac{1}{\sigma_1}} L_{\overline{ter}}^{\frac{1}{\sigma_2}} A_{\overline{sec}} L_{\overline{sec}}^{-\frac{1}{\sigma_2}} L_{\overline{sec}}^{\frac{1}{\sigma_3}} A_{non} L_{non}^{-\frac{1}{\sigma_3}} && \text{(B8)}\\
W_{pri} &= L^{\frac{1}{\sigma_1}} A_{\overline{ter}} L_{\overline{ter}}^{-\frac{1}{\sigma_1}} L_{\overline{ter}}^{\frac{1}{\sigma_2}} A_{\overline{sec}} L_{\overline{sec}}^{-\frac{1}{\sigma_2}} L_{\overline{sec}}^{\frac{1}{\sigma_3}} A_{pri} L_{pri}^{-\frac{1}{\sigma_3}} && \text{(B9)}
\end{aligned}
$$

Returns to Schooling The returns to schooling are:

$$r_{pri} = \ln\left(\frac{w_{pri}}{w_{non}}\right) = \ln\left(\frac{A_{pri}}{A_{non}}\right) - \frac{1}{\sigma_3}\ln\left(\frac{L_{pri}}{L_{non}}\right) \tag{B10}$$

$$r_{sec} = \ln\left(\frac{w_{sec}}{w_{pri}}\right) = \ln\left(\frac{A_{sec}}{A_{\overline{sec}}A_{pri}}\right) - \frac{1}{\sigma_2}\ln\left(\frac{L_{sec}}{L_{\overline{sec}}}\right) - \frac{1}{\sigma_3}\ln\left(\frac{L_{\overline{sec}}}{L_{pri}}\right) \tag{B11}$$

$$r_{ter} = \ln\left(\frac{w_{ter}}{w_{sec}}\right) = \ln\left(\frac{A_{ter}}{A_{\overline{ter}}A_{sec}}\right) - \frac{1}{\sigma_1}\ln\left(\frac{L_{ter}}{L_{\overline{ter}}}\right) - \frac{1}{\sigma_2}\ln\left(\frac{L_{\overline{ter}}}{L_{sec}}\right) \tag{B12}$$

B.2. Estimation

The Barro-Lee database allows me to observe L_{non}, L_{pri}, L_{sec}, and L_{ter}.[1] Meanwhile, the microdata allow me to estimate the returns to schooling r_{pri}, r_{sec}, and r_{ter}. The only elements that remain to be estimated are $L_{\overline{sec}}$, $L_{\overline{ter}}$, and the technology parameters A_{non}, A_{pri}, $A_{\overline{sec}}$, A_{sec}, $A_{\overline{ter}}$, and A_{ter}.

Let us assume without loss of generality that $A_{\overline{ter}} = 1 - A_{ter}$, $A_{\overline{sec}} = 1 - A_{sec}$, and $A_{non} = 1 - A_{pri}$. All parameters can then be recovered as follows.

First, rearranging equation B10, I recover A_{non} and A_{pri} from the return to primary education:

$$A_{non} = \frac{1}{1 + \exp\left(r_{pri} + \frac{1}{\sigma_3}\ln\left(\frac{L_{pri}}{L_{non}}\right)\right)} \tag{B13}$$

$$A_{pri} = 1 - A_{non} \tag{B14}$$

Second, I construct $L_{\overline{sec}}$:

$$L_{\overline{sec}} = \left(A_{non}L_{non}^{\frac{\sigma_3-1}{\sigma_3}} + A_{pri}L_{pri}^{\frac{\sigma_3-1}{\sigma_3}}\right)^{\frac{\sigma_3}{\sigma_3-1}} \tag{B15}$$

Third, I recover $A_{\overline{sec}}$ and A_{sec} from the return to secondary education:

$$A_{\overline{sec}} = \frac{1}{1 + A_{pri}\exp\left(r_{sec} + \frac{1}{\sigma_2}\ln\left(\frac{L_{sec}}{L_{\overline{sec}}}\right) + \frac{1}{\sigma_3}\ln\left(\frac{L_{\overline{sec}}}{L_{pri}}\right)\right)} \tag{B16}$$

$$A_{sec} = 1 - A_{\overline{sec}} \tag{B17}$$

[1] In a handful of cases, the share of workers with primary education or no schooling dropped to zero, leading counterfactual returns to schooling to diverge to infinity. To avoid these extreme cases, I impose a lower bound on the share of workers with primary education and no schooling of 1%.

Fourth, I construct $L_{\overline{ter}}$:

$$L_{\overline{ter}} = \left(A_{\overline{sec}} L_{\overline{sec}}^{\frac{\sigma_2 - 1}{\sigma_2}} + A_{sec} L_{sec}^{\frac{\sigma_2 - 1}{\sigma_2}} \right)^{\frac{\sigma_2}{\sigma_2 - 1}} \tag{B18}$$

Fifth, I recover $A_{\overline{ter}}$ and A_{ter} from the return to tertiary education:

$$A_{\overline{ter}} = \frac{1}{1 + A_{sec} \exp\left(r_{ter} + \frac{1}{\sigma_1} \ln\left(\frac{L_{ter}}{L_{\overline{ter}}} \right) + \frac{1}{\sigma_2} \ln\left(\frac{L_{\overline{ter}}}{L_{sec}} \right) \right)} \tag{B19}$$

$$A_{ter} = 1 - A_{\overline{ter}} \tag{B20}$$

Sixth, I construct L:

$$L = \left(A_{\overline{ter}} L_{\overline{ter}}^{\frac{\sigma_1 - 1}{\sigma_1}} + A_{ter} L_{ter}^{\frac{\sigma_1 - 1}{\sigma_1}} \right)^{\frac{\sigma_1}{\sigma_1 - 1}} \tag{B21}$$

All the parameters are now known: counterfactual output and wages can be directly calculated by plugging the 1980 distribution of educational attainment into equations B1 to B3.

B.3. Bringing the Model to the Microdata

Once all the parameters of the model are estimated, I bring it to the microdata. I construct the distributional growth accounting decomposition in four steps.

1) Downgrade Education Levels The starting point is individual-level data on wages and education. In each survey, I keep individuals aged 25 to 65, with no missing information on education and with positive personal income. Next, I match the microdata with information on the distribution of educational attainment of the working-age population by age group and gender in 1980 from the Barro-Lee database, covering four education levels: no schooling, incomplete or complete primary education, incomplete or complete secondary education, and incomplete or complete tertiary education. To move from observed educational attainment to counterfactual educational attainment, I randomly sample individuals and downgrade their education levels until matching 1980 totals in each country.

Individuals belonging to closest education categories are given priority in the simulation. For instance, if 20% of individuals had no schooling in 1980, compared to 10% today, I randomly sample 10% of individuals among the primary education group and downgrade their education level to no schooling. When closest education levels do not contain enough individuals (e.g., only 5% of individuals in this survey have primary education), I instead sample individuals from the category above (secondary education in this example). The outcome is a modified survey, in which the distribution of education corresponds to that observed in 1980. This survey contains "non-treated" observations, corresponding to individuals with unchanged education, as well as "treated" individuals whose education has been downgraded. This approach is very similar to the one recently adopted by Hershbein, Kearney, and Pardue (2020) to estimate the distributional effects of expanding access to college in the United States.

2) Adjust Wages The second step is to adjust the wages of "treated" and "non-treated" individuals. Since we are moving from the 2019 to the 1980 distribution of wages, the relevant parameter is the gap between the 2019 initial wage and the 1980 target wage. More specifically, consider an individual i with initial personal income $y_i(A^{2019}, L^{2019})$, whose education level is downgraded from s_2 to s_1. Their counterfactual income absent educational expansion is:

$$y_i(A^{2019}, L^{1980}) = \exp\left[\ln\left(y_i(A^{2019}, L^{2019})\right) - \ln\left(\frac{w_{s_2}(A^{2019}, L^{2019})}{w_{s_1}(A^{2019}, L^{1980})}\right)\right] \tag{B22}$$

Put simply, individual i see their income move from the actual wage of skill group s_2 to the counterfactual wage of skill group s_1. Actual and counterfactual wages are estimated above, so the calculation of this return is straightforward. For individuals whose education is downgraded by several levels, I use the corresponding cumulative returns. For instance, an individual downgraded from secondary education to no schooling will see their income decline by a return equal to $\frac{w_{sec}(A^{2019}, L^{2019})}{w_{non}(A^{2019}, L^{1980})}$.

Notice that because of imperfect substitution, non-treated workers are also affected by educational expansion. Typically, because educational expansion is associated with an increase in the supply of skilled workers, this implies that non-treated higher-educated workers see their wage increase, while non-treated lower-educated workers see their wage decrease in the counterfactual.

3) Derivation of Total Income The next step is to move from this counterfactual distribution of labor income to a counterfactual distribution of total income. I first aggregate actual labor income $y_L(A^{2019}, L^{2019})$ and counterfactual labor income $y_L(A^{2019}, L^{1980})$ in the survey microdata by decile, and calculate the corresponding log difference between actual income and counterfactual income by decile:

$$\psi^d = \ln y_L^d(A^{2019}, L^{2019}) - \ln y_L^d(A^{2019}, L^{1980}) \tag{B23}$$

This yields a measure of how much lower labor income would be if education had not improved.

I then incorporate these estimates into global income distribution data. I start with distributions from the World Inequality Database, which provide information on the average pretax income of each generalized percentile (all percentiles from p0 to p99, followed by a further decomposition of top incomes up to p99.999p100). I merge estimates of ψ^d by country-year-decile with this database.[2] I then calculate counterfactual total pretax income of generalized percentile p as:

$$y^p(A^{2019}, L^{1980}) = \exp\Big(\ln y^p(A^{2019}, L^{2019}) - \alpha^p \psi^p\Big) \tag{B24}$$

Where α^p is the capital income share of percentile p. Finally, I construct separate actual and counterfactual world distributions of income from 1980 to 2019, by ranking all individuals in the world by each income concept and aggregating average income by global generalized percentile.

4) Growth Accounting The final step is to calculate the share of growth accounted for by education for income group p:

$$\text{Share}_{\text{L}}^{\text{p,total}} = \frac{\ln y^p(A^{2019}, L^{2019}) - \ln y^p(A^{2019}, L^{1980})}{\ln y^p(A^{2019}, L^{2019}) - \ln y^p(A^{1980}, L^{1980})} \tag{B25}$$

[2]To get smoother profiles of counterfactual income by generalized percentile, I assume that ψ^d for each decile corresponds to the ratios observed for p5, p15, p25, p35, p45, p55, p65, p75, p85, and p95. I make the simplifying assumption that deciles of labor income are the same as deciles of total pretax income. I then interpolate ψ^d between percentiles to fill in missing values. I assume that values observed for percentiles within the bottom 5% and the top 5% are those observed for p5 and p95, respectively. Finally, I drop the bottom 5% in each country, which is by convention coded as having zero income in the World Inequality Database.

C. Natural Experiments

This appendix exploits evidence from three natural experiments to shed light on the aggregate and distributional effects of schooling. Section C.1 outlines the general econometric framework. Sections C.2, C.3, and C.4 turn to analyzing the Indian District Primary Education Program, the Indonesian INPRES school construction program, and U.S. compulsory schooling laws.

C.1. General Methodology

A large literature focuses on causally identifying individual returns to schooling. Less is known of its distributional effects at the level of regions or countries. This section attempts to shed some light on these effects in the context of three natural experiments. Consider the following empirical specification:

$$\ln y_{rt}^i = \gamma_0^i + \gamma_1^i S_{rt} + X_{rt}\beta + \delta_r + \delta_t + \varepsilon_{rt} \qquad \text{(C1)}$$

$$S_{rt} = \alpha_0 + \alpha_1 Z_{rt} + \eta_{rt} \qquad \text{(C2)}$$

Where i denotes income groups in subnational regions r at time t. The objective is to estimate the impact of increasing average regional schooling S_{rt} on $\ln y_{rt}^i$, the log average income of income group i. X_{rt} is a vector of controls, δ_r are subnational region fixed effects, and δ_t are time fixed effects.

The parameter of interest is γ_1^i, the semi-elasticity of average income of group i to regional average years of schooling. One option is to directly estimate equation C1 by OLS. Alternatively, average schooling S_{rt} can be instrumented using an instrument Z_{rt}, such as compulsory schooling laws. This approach has also been used to estimate human capital externalities, in particular in the case of U.S. compulsory schooling laws (Acemoglu and Angrist, 2000; Ciccone and Peri, 2006; Guo, Roys, and Seshadri, 2018). The main addition here is the focus on distributional effects, which amounts to estimating heterogeneous treatment effects by income group.

Estimating the distributional effects of educational expansion is empirically challenging, because it requires two sets of data that are rarely jointly available: data on the distribution of income within subnational regions, and an instrument that can predict quasi-random variation in regional schooling. Drawing on existing work, I study three such sources of variation: the India District Primary Education Program, the Indonesian School Construction Program, and U.S. state compulsory schooling laws.

C.2. India District Primary Education Program, 1994-2004

Context Between the 1990s and the beginning of the 2000s, India engaged in a massive expansion of public schooling, the District Primary Education Program (DPEP), targeting low-literacy regions. Districts with a female literacy rate below the national average were more likely to benefit from the policy. Exploiting this allocation rule, Khanna (2023) estimates the general equilibrium effects of the program using a regression discontinuity design. He finds a return to schooling of about 13% per year (after accounting for general equilibrium effects). General equilibrium effects induced by the greater relative supply of skilled workers depress returns by one-third, while indirectly benefiting unskilled workers.

Data and Empirical Specification I exploit data from the replication package provided by Khanna (2023). Exposure to the program is determined by district female literacy in 1991. Individual outcomes are obtained from the 2009 National Sample Survey (NSS), which covers wages and education at the district level. As in Khanna (2023), the sample is restricted to all adults aged 17 to 75 with positive wage income.

I then estimate the impact of the policy using the same regression discontinuity design as in the paper, comparing districts below and above the average female literacy rate. Optimal bandwidths are calculated using either the Calonico, Cattaneo, and Titiunik (2014) method or the Imbens and Kalyanaraman (2012) method (henceforth CCT and I and K, respectively). The main addition is that I focus on the effect of the program on the average wage of each wage quintile, yielding reduced-form estimates of the distributional incidence of primary education expansion.

Results Table C1 presents the results. Increasing district average years of schooling by one year is associated with a 0.12 log-point increase in wages in treated districts (CCT method). This effect is almost two times larger for the bottom 20% of earners. In contrast, the top 20% see their average wage decline, although the coefficient is not statistically significant. Results relying on the I and K method are similar, but the aggregate effect of educational expansion appears even larger. Aggregate returns to schooling estimated using this method are in the range of individual returns estimated by Khanna (2023), who finds returns of 0.16 (CCT) to 0.21 (I and K) log points using conventional 2SLS estimates, and 0.13 (CCT) after accounting for general equilibrium effects.

Table C2 compares the CCT estimates with simulated effects of expanding primary education, under different parametrizations of the return to schooling and the elasticity of substitution between skilled and unskilled workers. The simulation is done by upgrading the education of randomly sampled individuals from no schooling to primary education, increasing their earnings using the return to schooling, and finally adjusting relative wages for general equilibrium effects.

Simulated estimates fall close to the true effects of the policy. With a return of 16%, increasing average education by one year is associated with an increase in average wages of about 12%, which is identical to the actual effects. Distributional are also very similar to those estimated with the RD design. Both in the simulation and in the natural experiment, benefits appear relatively similar for the first four quintiles and significantly lower for the top 20%. This can be rationalized by the fact that in India, workers with no schooling and workers with basic education are both prevalent among the bottom 80% of the distribution, so that upgrading some workers from no schooling to basic education benefits this entire group.

C.3. Indonesia School Construction Program, 1973-1978

Context Between 1973 and 1978, Indonesia engaged in a massive school construction program expanding access to basic education. Exploiting differences in exposure to newly built schools across cohorts and regions, Duflo (2001) estimates individual returns to schooling ranging from 7% to 11%. A number of studies have updated and extended her analysis since then, focusing on intergenerational effects (Akresh, Halim, and Kleemans, 2023), structural transformation (Karachiwalla and Palloni, 2019), or rural-urban migration (Hsiao, 2023). Duflo (2004) also moves beyond individual outcomes to focus on spillovers of the program to non-treated groups. Her analysis shows mixed findings, suggesting a decline in the wages of non-treated groups, but an increase in employment in the formal sector.

Data Drawing on the work of Duflo (2004), I exploit exposure to the program by district to estimate the aggregate and distributional effects of primary education expansion. My analysis expands her work in two ways. First, I expand the time coverage, which increases statistical power and allows me to get closer to long-run effects. To do so, I harmonize every round of the SUSENAS, a household survey covering about a million individuals every year, from 1993 to 2019. This allows me to construct a balanced panel of 230 districts with annual data on education, the distribution of consumption, and other sociodemographic variables.[3] Second, I study the effects of the program on total district consumption and its distribution by consumption quintile, while Duflo (2004) focuses on spillover effects on older cohorts. The sample is

[3] Some districts have undergone splits and merges. I rely on crosswalks provided by Roodman (2022) to ensure consistent boundaries over time.

restricted to all adults aged 15 to 70. Consumption is split equally between all household members.

Empirical Specification The empirical specification is given by equation C1. I estimate the effect of average years of schooling in district r on the log average consumption of decile i, controlling for district and year fixed effects. Average years of schooling is instrumented by the interaction between survey years and the number of schools built per 5-14 population between 1974 and 1978, as in Duflo (2004).[4] The school construction program is thus taken as an instrument for differential trends in the education of the working-age population across districts from 1993 to 2019. The identification assumption, analogous to Duflo (2004), is that there is no unobserved shock both correlated with the program and affecting household expenditure during that period.

Results Table C3 presents the main results. The baseline specification controls for the demographic and gender composition of each district, the share of college graduates, and district and year fixed effects. The aggregate return to schooling is about 9%. This effect is almost four times larger for the bottom quintile (0.22 log points) than for the top quintile (0.058). Columns 4 to 6 add controls for 1971 primary school enrollment and water and sanitation spending interacted with survey year, as in Duflo (2004). These estimates are underpowered, but the results are qualitatively similar. Columns 7 to 9 further add controls for 1971 child population and population density interacted with survey year. This model is even more underpowered, but the point estimates remain very similar. The coefficient on the average income of the bottom 20% remains large and statistically significant. While the sample size is not sufficient to precisely estimate aggregate returns to schooling, the progressive nature of the policy stands out across all specifications.

Table C4 compares the benchmark estimates to simulated effects of the policy using the 1996 Indonesian labor force survey (SAKERNAS). The simulation is done exactly as in the Indian case, upgrading the education of randomly sampled individuals from no schooling to primary education, increasing their earnings using the return to schooling, and finally adjusting relative wages. As in India, the simulation does a good job at reproducing results from the natural experiment. The expansion of primary education is estimated to be progressive in all specifications, with orders of magnitude similar to those found in the data.

[4] Given significant noise introduced by the low sample size available for each district-year cell, I specify survey years as a continuous variable in the first stage. Indeed, we should expect the program to have introduced smooth, secular differential trends in educational expansion. Constraining the interaction of survey years and treatment intensity to follow such a secular trend makes the results less sensitive to different empirical strategies.

C.4. U.S. Compulsory Schooling Laws, 1875-1961

Context Between the mid-19th and the mid-20th century, U.S. states gradually implemented laws limiting child labor and enforcing compulsory school attendance. The effects of these laws were first studied by Acemoglu and Angrist (2000), who combined data on 1914-1965 laws with census microdata to estimate the magnitude of human capital spillovers. Their analysis gave rise to a rich literature exploiting compulsory schooling laws to estimate individual returns to schooling (Clay, Lingwall, and Stephens, 2021; Stephens and Yang, 2014), elasticities of substitution between skill groups (Ciccone and Peri, 2006), and human capital externalities (Ciccone and Peri, 2006; Guo, Roys, and Seshadri, 2018; Iranzo and Peri, 2009).

Data My analysis extends previous work in two ways. First, I study the aggregate and distributional effects of educational expansion, while existing studies focus on dimensions of these effects separately. Second, I exploit recently compiled data by Clay, Lingwall, and Stephens (2021), covering compulsory schooling laws over the entire 1875-1961 period. This represents an important improvement over the previous literature, which only covered laws implemented after 1915. I rely on the 1940 to 2000 census microdata samples available from IPUMS, which cover personal income, state of birth, state of residence, education, and other sociodemographic variables. The sample is restricted to all adults aged 25 to 65 with positive personal income (wage income in 1940) living in the contiguous United States.

Empirical Specification As in the Indian and Indonesian cases, I regress the average income of each personal income decile on average state schooling, instrumented by compulsory schooling laws. I use the following instrument for average years of schooling S_{st} in state s at time t:

$$S_{st} = \pi_0 + \pi_1 \sum_c \sum_{s'} N_{css't} RS_{cs'} + \theta_s + \theta_t + u_{st} \tag{C3}$$

$RS_{cs'}$ is required years of schooling for cohort c born in state s', $N_{css't}$ is the number of individuals living in state s at time t who were born in state s', and θ_s and θ_t are state and year fixed effects. Required years of schooling correspond to the time a children born in a given year is required to stay in school, calculated by combining information on required attendance at each year of life (see Clay, Lingwall, and Stephens, 2021; Stephens and Yang, 2014). The instrument is thus average *required* years of schooling of the working-age population, calculated by averaging required years across all cohort-state-of-birth cells, weighted by their populations. This approach is analogous to the one recently adopted by Guo, Roys, and Seshadri (2018).

Results Table C5 presents the main results. In the baseline specification, the aggregate return to schooling is 0.16 log points. The corresponding values are 0.44 for the bottom 20% and 0.05 for the top 20%. Education thus appears as a powerful driver of inequality reduction, even more so in the U.S. than in India and Indonesia. Adding interacted census region and year fixed effects leaves the results almost unchanged (columns 4 to 6). Columns 7 to 9 further add controls for initial conditions. The aggregate effect is slightly lower and the estimates are unsurprisingly underpowered. Even under this highly demanding specification, however, the coefficient on the bottom 20% remains large and statistically significant.

Table C6 compares observed and simulated effects of the policy. The simulation is done by upgrading the education of randomly sampled individuals with either no schooling or primary education to secondary education, given that required years of schooling range from 0 to 9 years. Here, the model appears to strongly underestimate the aggregate and inequality-reducing effects of the policy, even with a return to schooling of 16% and an elasticity of substitution of 2.

There are at least three reasons that could explain this finding. First, state compulsory schooling laws extended both primary and secondary school attendance, with significant variations in timing and intensity across states. This makes it more difficult to accurately simulate the overall effect of these policies. Second, there is evidence that returns to schooling were substantially higher at the bottom of the income distribution during the first wave of compulsory schooling laws (Clay, Lingwall, and Stephens, 2021). The simulation assumes a constant return by income group, which by construction limits its ability to capture higher returns for low-income earners. Third, recent evidence points to large human capital externalities from schooling expansion in the United States (Guo, Roys, and Seshadri, 2018). This might explain why the simulation ends up strongly underestimating the aggregate return to schooling in this context.

Table C1 – India DPEP: Aggregate and Distributional Effects of Schooling

	Bandwidth Selection: CCT Method			Bandwidth Selection: I and K Method		
	Average Income	Bottom 20% Income	Top 20% Income	Average Income	Bottom 20% Income	Top 20% Income
Average Years of Schooling	0.117*	0.207***	-0.092	0.257***	0.316***	0.012
	(0.061)	(0.059)	(0.071)	(0.058)	(0.058)	(0.068)
N	46314	9007	9515	46314	9007	9515

Notes. The table reports the effect of district average years of schooling on district average income, the average of the bottom 20%, and the average income of the top 20%. Bandwidths: "CCT" indicates the Calonico, Cattaneo, and Titiunik (2014) method, "I and K" the Imbens and Kalyanaraman (2012) method. Data from Khanna (2023). Standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C2 – India DPEP: Actual vs. Simulated Effects of Educational Expansion

	Parameters		Effect of Increasing Average District Schooling by One Year (%)					
	Return to Schooling	Elasticity of Substitution	Average Income	Q1	Q2	Q3	Q4	Q5
Actual Effect			12.4	23.0	11.9	18.7	21.3	-8.8
Simulated Effect	13%	∞	9.3	17.5	13.5	14.9	10.0	5.6
	13%	6	9.3	19.3	13.4	14.9	10.0	5.5
	13%	4	9.3	20.2	13.4	14.8	10.0	5.4
	13%	2	9.3	22.7	12.9	14.9	9.9	5.2
	16%	∞	12.4	19.0	15.1	18.6	14.4	8.4
	16%	6	12.4	21.0	15.1	18.7	14.3	8.1
	16%	4	12.4	22.0	15.0	18.7	14.3	8.0
	16%	2	12.4	25.0	14.8	19.0	14.3	7.7
	20%	∞	17.1	20.1	16.6	22.1	21.2	13.5
	20%	6	17.1	22.4	16.9	22.4	21.1	13.1
	20%	4	17.1	23.6	17.0	22.5	21.1	12.9
	20%	2	17.1	27.0	17.1	23.1	20.9	12.4

Notes. Actual effect: estimated effect of the policy on average district income and the average income of each wage quintile, using data from Khanna (2023). Simulated effect: effect of the policy predicted using 2019 LFS data, under different assumptions on the return to a year of schooling and the elasticity of substitution between skilled and unskilled workers.

Table C3 – Indonesia INPRES: Aggregate and Distributional Effects of Schooling

	Baseline			+ Controlling for 1971 Primary School Enrollment and Water & Sanitation Spending			+ Controlling for 1971 Child Population and Population Density		
	Average Income	Bottom 20% Income	Top 20% Income	Average Income	Bottom 20% Income	Top 20% Income	Average Income	Bottom 20% Income	Top 20% Income
Average Years of Schooling	0.087***	0.220***	0.058*	0.133	0.505***	-0.002	0.084	0.445**	-0.029
	(0.026)	(0.035)	(0.031)	(0.083)	(0.145)	(0.097)	(0.108)	(0.179)	(0.131)
First-Stage F-Stat	174.56	174.56	174.56	18.32	18.32	18.32	10.53	10.53	10.53
N	5520	5520	5520	5352	5352	5352	5304	5304	5304

Notes. The table reports the effect of regency average years of schooling on regency average income, the average income of the bottom 20%, and the average income of the top 20%. Columns 1 to 3 control for the demographic composition of the regency, the share of women, and the share of workers with tertiary education. Columns 4 to 6 add controls for 1971 primary school enrollment rates and water and sanitation spending, interacted with survey year. Columns 7 to 9 further add controls for the share of the population aged 5 or below in 1971 and population density in 1971, interacted with survey year. Data from Duflo (2001) and Roodman (2022). Standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C4 – Indonesia INPRES: Actual vs. Simulated Effects of Educational Expansion

	Parameters		Effect of Increasing Average District Schooling by One Year (%)					
	Return to Schooling	Elasticity of Substitution	Average Income	Q1	Q2	Q3	Q4	Q5
Actual Effect			9.1	24.6	16.7	12.2	8.4	6.0
Simulated Effect	9%	∞	5.7	15.4	10.7	5.3	4.6	4.0
	9%	6	5.7	19.2	11.7	6.4	5.2	3.7
	9%	4	5.7	20.5	12.3	7.1	5.5	3.5
	9%	2	5.7	25.6	13.9	4.4	3.2	3.0
	11%	∞	7.7	17.3	12.9	7.7	7.3	5.7
	11%	6	7.7	20.7	13.9	7.5	7.1	5.4
	11%	4	7.7	22.6	14.6	8.6	7.8	5.3
	11%	2	7.7	28.2	16.5	6.0	5.8	5.1
	13%	∞	10.5	18.9	15.2	9.6	10.1	8.9
	13%	6	10.5	22.2	15.9	9.3	9.8	8.6
	13%	4	10.5	24.1	16.3	9.0	9.7	8.6
	13%	2	10.5	29.1	18.7	7.6	8.2	8.2

Notes. Actual effect: estimated effect of the policy on average district income and the average income of each wage quintile, using data from Duflo (2001). Simulated effect: effect of the policy predicted using 1996 SAKERNAS microdata, under different assumptions on the return to a year of schooling and the elasticity of substitution between skilled and unskilled workers.

Table C5 – U.S. Compulsory Schooling Laws: Aggregate and Distributional Effects of Schooling

	Baseline			+ Census Region × Year FE			+ Controls for 1940 Educational Attainment and Average Income × Year FE		
	Average Income	Bottom 20% Income	Top 20% Income	Average Income	Bottom 20% Income	Top 20% Income	Average Income	Bottom 20% Income	Top 20% Income
Average Years of Schooling	0.157***	0.437***	0.050*	0.147***	0.431***	0.079*	0.082	0.272**	0.063
	(0.032)	(0.095)	(0.027)	(0.045)	(0.110)	(0.044)	(0.051)	(0.114)	(0.057)
First-Stage F-Stat	87.05	87.05	87.05	19.01	19.01	19.01	12.10	12.10	12.10
N	343	343	343	343	343	343	343	343	343

Notes. The table reports the effect of state average years of schooling on state average income, the average income of the bottom 20%, and the average income of the top 20%. Columns 1 to 3 control for the demographic, gender, and racial composition of each state, as well as the share of workers with tertiary education. Columns 4 to 6 add census region × year fixed effects. Columns 7 to 9 further add controls for 1940 average years of schooling and average personal income, interacted with survey year dummies. Data from IPUMS census microdata combined with information on compulsory schooling laws from Acemoglu and Angrist (2000) and Clay, Lingwall, and Stephens (2021). Standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C6 – U.S. Compulsory Schooling Laws: Actual vs. Simulated Effects of Educational Expansion

	Parameters		Effect of Increasing Average State Schooling by One Year (%)					
	Return to Schooling	Elasticity of Substitution	Average Income	Q1	Q2	Q3	Q4	Q5
Actual Effect			16.9	54.9	58.4	29.6	13.1	5.1
Simulated Effect	8%	∞	4.5	17.5	9.7	5.2	3.6	2.8
	8%	6	4.5	21.1	11.4	5.7	3.3	2.1
	8%	4	4.5	22.8	12.3	6.0	3.2	1.8
	8%	2	4.5	28.0	14.9	6.8	2.8	0.9
	12%	∞	7.4	24.2	14.1	7.6	5.5	6.0
	12%	6	7.4	27.7	15.8	8.2	5.3	5.3
	12%	4	7.4	29.5	16.7	8.5	5.2	4.9
	12%	2	7.4	34.8	19.2	9.3	4.7	4.0
	16%	∞	11.0	29.5	18.4	9.7	7.5	10.6
	16%	6	11.0	33.1	20.2	10.3	7.2	9.9
	16%	4	11.0	34.9	21.1	10.6	7.1	9.6
	16%	2	11.0	40.2	23.6	11.4	6.7	8.6

Notes. Actual effect: estimated effect of the policy on average state income and the average income of each personal income quintile, combining IPUMS census microdata with information on compulsory schooling laws from Acemoglu and Angrist (2000) and Clay, Lingwall, and Stephens (2021). Simulated effect: effect of the policy predicted using 1960 census microdata, under different assumptions on the return to a year of schooling and the elasticity of substitution between skilled and unskilled workers.

D. Robustness Checks and Sensitivity Analysis

D.1. Causal Estimates of the Returns to Schooling

A New Compilation of IV Returns to Schooling In an alternative specification, I rely on instrumental variable estimates of the returns to schooling collected from a number of existing studies. Surveying the literature, I was able to find 62 studies exploiting natural experiments to estimate the causal effect of education on earnings. Table D1 provides a complete list of these articles, together with the type of policy, the corresponding education level, and the estimated coefficients and standard errors when available.

This article is interested in the effect of educational attainment on earnings. I thus start by excluding studies that do not allow estimating a Mincerian return to completed years of schooling. This is the case of 15 studies that focused on compulsory schooling laws in France, Germany, the Netherlands, and the United Kingdom. These studies have one thing in common: either the policy studied did not lead to an increase in educational attainment, or the data used by the authors did not cover completed years of schooling. In the United Kingdom, for instance, ten studies estimated returns to compulsory schooling using the school leaving age as the explanatory variable. Yet the leaving age can differ significantly from educational attainment, as documented for instance by Grenet (2013) in the case of France's 1967 Berthoin reform, which increased the age at which French students left school but had not effect on attainment. As a result, it is unclear whether zero returns found in some of these papers reflect the failure of the policy to raise attainment or the actual absence of a return to educational attainment. For this reason, I exclude these studies focusing on UK reforms, as well as the two French and UK reforms studied by Grenet (2013), who also reports returns as a function of the leaving age but not as a function of completed years of schooling. Similarly, Pischke (2007) finds no effect of a reform lengthening the school year on attainment in Germany, while the data used in Pischke and Wachter (2008) do not allow them to study the effect of German compulsory schooling on educational attainment (their first stage is based on the secondary school graduation year). Oosterbeek and Webbink (2007) study the effect of a compulsory schooling law in the Netherlands, but do not observed educational attainment in their dataset either. I also exclude studies that do not have sufficient statistical power to rule out either zero or large returns (Duflo, Dupas, and Kremer, 2024; Filmer and Schady, 2014).

This leaves us with a collection of 46 studies. Among these, 13 report an IV estimate of the return to schooling, but do not report an OLS estimate for comparison. My comparison of OLS and IV returns thus ends up covering 33 separate studies.

Discussion IV estimates of the returns to schooling have two key advantages: they are causally identified, and they focus on newly skilled workers. Exploiting the results of these studies in my analysis is not without difficulties, however, for at least four reasons.

First, these studies cover specific populations, which marginally gained access to education as a result of each policy. These populations may be different from the average newly skilled worker in a given country.

Second, each study covers a specific education level. This implies that the IV return reflects the return to gaining access to a specific level, while the OLS return reflects the average return across all levels. Depending on the convexity of returns, the gap between the degree-specific and average return can be large. In particular, most studies covered in this collection expanded access to basic education. In the presence of convex returns, this would imply that the IV-OLS gap is underestimated.

Third, studies estimate the IV return to schooling among workers falling into specific age ranges. Treated groups are younger than the average worker in many studies. In the presence of growing education premiums over the life-cycle, this implies that IV returns may substantially underestimate the lifetime economic benefits of schooling (Bhuller, Mogstad, and Salvanes, 2017).

Fourth, education policies may have spillovers over non-treated groups due to general equilibrium effects. In the presence of imperfect substitutability across skill and age groups, the typical IV estimate of the return to schooling will be biased (Khanna, 2023). Given large variations in the scale of education policies across articles, it is hard to conclude on the significance of these general equilibrium effects.

Bringing the Model to the Microdata with IV Returns to Schooling With these limitations in mind, I investigate the sensitivity of my results to using IV returns to schooling instead of Mincerian returns estimated by OLS. I start by exploiting the ratio of IV to OLS returns to schooling estimated in each study to correct OLS returns to schooling estimated with my data. Let r_{cj}^{OLS} be the OLS return to schooling estimated for country c and education level j, r_{cj}^{IV} the IV return estimated in the same paper, and $\hat{r}_{cj}^{OLS}$ the OLS return estimated with my microdatabase. I construct "IV-corrected" returns to schooling as:

$$\hat{r}_{cj}^{IV} = \hat{r}_{cj}^{OLS} \times \frac{r_{cj}^{IV}}{r_{cj}^{OLS}} \tag{D1}$$

Hence, I correct OLS returns estimated with my data using country-education-level-specific adjustment factors derived from the comparison of OLS and IV returns found in each paper. This allows me to adjust returns to schooling in 23 countries representative of about two-thirds of the world's population.

I then adjust OLS returns to schooling in missing countries. For European countries not covered by any study, I use the 1.33 correction factor found in Brunello, Weber, and Weiss (2015), who estimate the returns to schooling in Europe by combining information on various European compulsory schooling laws. For other countries, I use the average correction factor by education level found across studies. This amounts to multiplying the returns to primary, secondary, and tertiary education by about 1.4, 1.3, and 2, respectively.

Finally, I construct the distributional growth accounting decomposition using these returns. First, I downgrade education levels in each survey until reaching the 1980 counterfactual, as in the rest of the paper. Second, I reduce earnings of "treated" individuals using these "IV-corrected" returns to schooling. Third, I aggregate actual and counterfactual income by decile. Finally, I adjust relative counterfactual incomes by decile so that they match relative incomes predicted by the model. In other words, the only difference between this specification and my main results is that the *aggregate* effects of education in each country are captured by the "IV-corrected" returns rather than by wage adjustments predicted by the model. Distributional effects of schooling are kept identical in the two specifications.

D.2. Alternative Elasticities and Production Functions

CES Production Function With Alternative Nesting Structure The production function is:

$$H = \left(A_{low} L_{low}^{\frac{\sigma_1 - 1}{\sigma_1}} + A_{upp} L_{upp}^{\frac{\sigma_1 - 1}{\sigma_1}}\right)^{\frac{\sigma_1}{\sigma_1 - 1}} \tag{D2}$$

$$L_{low} = \left(A_{non} L_{non}^{\frac{\sigma_2 - 1}{\sigma_2}} + A_{pri} L_{pri}^{\frac{\sigma_2 - 1}{\sigma_2}}\right)^{\frac{\sigma_2}{\sigma_2 - 1}} \tag{D3}$$

$$L_{upp} = \left(A_{sec} L_{sec}^{\frac{\sigma_3 - 1}{\sigma_3}} + A_{ter} L_{ter}^{\frac{\sigma_3 - 1}{\sigma_3}}\right)^{\frac{\sigma_3}{\sigma_3 - 1}} \tag{D4}$$

Returns to primary, secondary, and tertiary education are:

$$r_{pri} = \ln\left(\frac{w_{pri}}{w_{non}}\right) = \ln\left(\frac{A_{pri}}{A_{non}}\right) - \frac{1}{\sigma_2}\ln\left(\frac{L_{pri}}{L_{non}}\right) \tag{D5}$$

$$r_{sec} = \ln\left(\frac{w_{sec}}{w_{pri}}\right) = \ln\left(\frac{A_{upp}}{A_{low}}\right) + \ln\left(\frac{A_{sec}}{A_{pri}}\right) - \frac{1}{\sigma_1}\ln\left(\frac{L_{upp}}{L_{low}}\right) - \frac{1}{\sigma_3}\ln\left(\frac{L_{sec}}{L_{upp}}\right) - \frac{1}{\sigma_2}\ln\left(\frac{L_{low}}{L_{pri}}\right) \tag{D6}$$

$$r_{ter} = \ln\left(\frac{w_{ter}}{w_{sec}}\right) = \ln\left(\frac{A_{ter}}{A_{sec}}\right) - \frac{1}{\sigma_3}\ln\left(\frac{L_{ter}}{L_{sec}}\right) \tag{D7}$$

Let $A_{upp} = 1 - A_{low}$, $A_{pri} = 1 - A_{non}$ and $A_{ter} = 1 - A_{sec}$. The model can then be solved in four steps.

First, recover technology parameters within each nest:

$$
\begin{aligned}
A_{non} &= \frac{1}{1+\exp\left(r_{pri}+\frac{1}{\sigma_2}\ln\left(\frac{L_{pri}}{L_{non}}\right)\right)} && \text{(D8)}\\
A_{pri} &= 1-A_{non} && \text{(D9)}\\
A_{sec} &= \frac{1}{1+\exp\left(r_{sec}+\frac{1}{\sigma_3}\ln\left(\frac{L_{ter}}{L_{sec}}\right)\right)} && \text{(D10)}\\
A_{ter} &= 1-A_{sec} && \text{(D11)}
\end{aligned}
$$

Second, use these parameters to construct L_{low} and L_{upp}. Third, recover A_{low} and A_{upp}:

$$
\begin{aligned}
A_{low} &= \frac{1}{1+\exp\left(r_{sec}-\ln\left(\frac{A_{sec}}{A_{pri}}\right)+\frac{1}{\sigma_1}\ln\left(\frac{L_{upp}}{L_{low}}\right)+\frac{1}{\sigma_3}\ln\left(\frac{L_{sec}}{L_{upp}}\right)+\frac{1}{\sigma_2}\ln\left(\frac{L_{low}}{L_{pri}}\right)\right)} && \text{(D12)}\\
A_{upp} &= 1-A_{low} && \text{(D13)}
\end{aligned}
$$

Fourth, use these parameters to construct H.

CES Production Function With No Nest I also consider a CES production function with no nest:

$$
H=\left(A_{non}L_{non}^{\frac{\sigma-1}{\sigma}}+A_{pri}L_{pri}^{\frac{\sigma-1}{\sigma}}+A_{sec}L_{sec}^{\frac{\sigma-1}{\sigma}}+A_{ter}L_{ter}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}
$$

Returns to primary, secondary, and tertiary education are:

$$
\begin{aligned}
r_{pri} &= \ln\left(\frac{w_{pri}}{w_{non}}\right)=\ln\left(\frac{A_{pri}}{A_{non}}\right)-\frac{1}{\sigma}\ln\left(\frac{L_{pri}}{L_{non}}\right)\\
r_{sec} &= \ln\left(\frac{w_{sec}}{w_{pri}}\right)=\ln\left(\frac{A_{sec}}{A_{pri}}\right)-\frac{1}{\sigma}\ln\left(\frac{L_{sec}}{L_{pri}}\right)\\
r_{ter} &= \ln\left(\frac{w_{ter}}{w_{sec}}\right)=\ln\left(\frac{A_{ter}}{A_{sec}}\right)-\frac{1}{\sigma}\ln\left(\frac{L_{ter}}{L_{sec}}\right)
\end{aligned}
$$

The model can be estimated in two steps. First, recover technology parameters, normalizing A_{non} to 1:

$$
\begin{aligned}
A_{non} &= 1 \\
A_{pri} &= \exp\left(r_{pri} + \frac{1}{\sigma} \ln\left(\frac{L_{pri}}{L_{non}} \right) \right) \\
A_{sec} &= \exp\left(\ln(A_{pri}) + r_{sec} + \frac{1}{\sigma} \ln\left(\frac{L_{sec}}{L_{pri}} \right) \right) \\
A_{ter} &= \exp\left(\ln(A_{sec}) + r_{ter} + \frac{1}{\sigma} \ln\left(\frac{L_{ter}}{L_{sec}} \right) \right)
\end{aligned}
$$

Second, construct H using these parameters.

CES Production Function With Imperfect Substitution Between Age Groups I also consider an extension in which workers belonging to different age groups are imperfectly substitutable. For simplicity, I consider a single elasticity across skill groups σ and a single elasticity across age groups λ. The production function is:

$$
H = \left(A_{non} L_{non}^{\frac{\sigma-1}{\sigma}} + A_{pri} L_{pri}^{\frac{\sigma-1}{\sigma}} + A_{sec} L_{sec}^{\frac{\sigma-1}{\sigma}} + A_{ter} L_{ter}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{D14}
$$

Each skill group i is composed of workers belonging to different age groups:

$$
L_i = \left(A_{ia} L_{ia}^{\frac{\lambda-1}{\lambda}} + A_{ib} L_{ib}^{\frac{\lambda-1}{\lambda}} + A_{ic} L_{ic}^{\frac{\lambda-1}{\lambda}} + A_{id} L_{id}^{\frac{\lambda-1}{\lambda}} \right)^{\frac{\lambda}{\lambda-1}} \tag{D15}
$$

Where a, b, c, and d refer to workers aged 25 to 34, 35 to 44, 45 to 54, and 55 and above, respectively. It is straightforward to solve this model using the same steps as in the previous sections. The wage of a worker belonging to skill group i and age group j is given by:

$$
W_{ij} = H^{\frac{1}{\sigma}} A_i L_i^{-\frac{1}{\sigma}} L_i^{\frac{1}{\lambda}} A_{ij} L_{ij}^{-\frac{1}{\lambda}} \tag{D16}
$$

The return to experience for group j compared to group j' is:

$$
r_{jj'} = \ln\left(\frac{w_{ij}}{w_{ij'}} \right) = \ln\left(\frac{A_{ij}}{A_{ij'}} \right) - \frac{1}{\lambda} \ln\left(\frac{L_{ij}}{L_{ij'}} \right) \tag{D17}
$$

I solve this model and bring it to the microdata in six steps.

First, I run OLS regressions relating the log of personal income to dummies for belonging to these different age groups, controlling for education and gender. This allows me to recover estimates of the returns to experience $r_{jj'}$ for the different age groups in each country.

Second, I recover age-specific productivity parameters A_{ij} from equation D17. To measure L_{ij} in each country, I rely on the Barro-Lee database, which records the number of workers belonging to different skill and age groups in each country. I assume an elasticity of substitution across age groups of $\lambda = 5$ (e.g., Card and Lemieux, 2001; Fernández and Messina, 2018; Khanna, 2023).

Third, once A_{ij} are known, I construct L_i for the different skill groups.

Fourth, I recover technology parameters A_i for the different skill groups, using estimates of the returns to schooling as in the rest of the paper.

Fifth, I construct actual output and counterfactual output absent educational expansion and demographic change, replacing labor supplies by their 1980 counterparts. Notice that I replace the entire distribution of workers by skill and age group by its 1980 value. This counterfactual thus incorporates both returns to education and returns to experience.

Sixth, I bring the model to the microdata, using the same methodology as in the rest of the paper. The main difference here is that workers see both their education and their age change in the counterfactual. Their wage thus ends up affected by both skill supply and age supply effects, which are governed by these two elasticities. The outcome of this exercise is a counterfactual distribution of income absent both educational expansion and demographic change.

D.3. Within-Category Heterogeneity in Human Capital

My main specification assumes that workers are homogeneous within each of the four skill groups (no schooling, primary, secondary, and tertiary). In this section, I consider an extension of the model in which human capital is allowed to vary within each education category.

Model My analysis follows Caselli (2016). Workers are imperfectly substitutable across the four groups, while workers within each category are perfectly substitutable but may still have different human capital levels. More specifically, let us rewrite equations 15 to 17:

$$H = \left(A_{\overline{ter}} L_{\overline{ter}}^{\frac{\sigma_1 - 1}{\sigma_1}} + A_{ter} L_{ter}^{\frac{\sigma_1 - 1}{\sigma_1}} \right)^{\frac{\sigma_1}{\sigma_1 - 1}} \tag{D18}$$

$$L_{\overline{ter}} = \left(A_{\overline{sec}} L_{\overline{sec}}^{\frac{\sigma_2 - 1}{\sigma_2}} + A_{sec} L_{sec}^{\frac{\sigma_2 - 1}{\sigma_2}} \right)^{\frac{\sigma_2}{\sigma_2 - 1}} \tag{D19}$$

$$L_{\overline{sec}} = \left(A_{non} L_{non}^{\frac{\sigma_3 - 1}{\sigma_3}} + A_{pri} L_{pri}^{\frac{\sigma_3 - 1}{\sigma_3}} \right)^{\frac{\sigma_3}{\sigma_3 - 1}} \tag{D20}$$

My benchmark specification assumes $L_{pri} = L_{pri1} + L_{pri2}$ and $L_{sec} = L_{sec1} + L_{sec2}$, where L_{pri1}, L_{pri2}, L_{sec1}, and L_{sec2} refer to the share of workers with incomplete primary education, complete primary education, incomplete secondary education, and complete secondary education, respectively. I now consider an extension in which these groups are allowed to hold different human capital, as in Caselli (2016):

$$L_{pri} = L_{pri1} + e^{r_{pri2}} L_{pri2} \tag{D21}$$

$$L_{sec} = L_{sec1} + e^{r_{sec2}} L_{sec2} \tag{D22}$$

Where r_{pri2} and r_{sec2} are the returns to completing primary and secondary education with respect to holding incomplete degrees, respectively. In the absence of data on incomplete versus complete tertiary education, I continue to assume that workers with tertiary education are homogeneous. My main results correspond to the case where $r_{pri2} = r_{sec2} = 0$: increasing the share of workers with complete relative to incomplete secondary education has no effect on output. In this extended model, in contrast, doing so increases output as long as the return to completing secondary education is positive.

Empirical Application I bring this model to the data using surveys covering sufficiently detailed information on educational attainment. Unfortunately, the ILO microdata do not provide information on incomplete versus complete degrees. For this, I turn to the I2D2 database. I searched for all surveys fielded after 2015 that cover the required information. I was able to identify such surveys for 79 countries. Of these, only 37 have sufficiently large sample sizes to obtain reliable estimates of the returns to completing primary and secondary education versus holding incomplete degrees. My analysis therefore focuses on these countries.

I estimate returns to schooling using the following modified Mincerian equation:

$$\ln y_i = \alpha + \beta_{pri1} D_{i,pri1} + \beta_{pri2} D_{i,pri2} + \beta_{sec1} D_{i,sec1} + \beta_{sec2} D_{i,sec2} + \beta_{ter} D_{i,ter} + X_i \beta + \varepsilon_i \tag{D23}$$

Where y_i is total annual earned income from all jobs of individual i in a given country, $D_{i,pri1}$, $D_{i,pri2}$, $D_{i,sec1}$, $D_{i,sec2}$, and $D_{i,ter}$ are dummies for having reached incomplete primary, complete primary, incomplete secondary, complete secondary, and tertiary education, and X_i is a vector of controls including gender, an age quartic, and interactions between gender and the age quartic.

Returns to completing primary and secondary education are:

$$r_{pri2} = \beta_{pri2} - \beta_{pri1} \tag{D24}$$

$$r_{sec2} = \beta_{sec2} - \beta_{sec1} \tag{D25}$$

All other ingredients of the model stick to the benchmark specification. In particular, technology terms can be recovered from the same estimates of returns to primary, secondary, and tertiary education as in the rest of the paper. The share of workers with incomplete versus complete degrees is taken from the Barro-Lee database. All parameters are then known and one can estimate counterfactual wages and output.

Results Figure D1 compares schooling gains estimated with the benchmark versus extended models. Table D5 reports detailed results by country. In the average country, the return to completing primary education versus not completing it is 14%, while the return to completing secondary education is 27%. Annualized schooling gains are 1% in the benchmark model versus 1.1% in the extended model. The share of growth explained by education is 39% versus 43%. As shown in Figure D1, all countries are very close to the 45-degree line: accounting for within-category variations in human capital barely affects cross-country differences in schooling gains.

If anything, the extended model predicts slightly larger effects of educational expansion. The reason for this is that the relative shares of workers with complete degrees has increased. In the average country, 47% of primary-educated workers had complete degrees in 1980, compared to 74% in 2019. 26% of secondary-educated workers had complete degrees in 1980, compared to 54% in 2019. My benchmark specification treats these changes as having no implication for economic growth, while the extended model does account for the resulting positive returns. The returns to completing primary and secondary education are low, however, which is why this refinement barely affects estimates of the overall contribution of education.

D.4. Heterogeneous Educational Expansion by Socioeconomic Characteristic

In my main specification, I randomly sample individuals and downgrade their education by age-gender cell. In this section, I investigate the implications of further refining the analysis by accounting for heterogeneous educational expansion by socioeconomic characteristic other than age and gender.

I focus on three countries with available data: India, South Africa, and the United States. I compare three specifications in each country. The first one downgrades education levels of individuals without any heterogeneity, the second one accounts for heterogeneous educational expansion by age and gender, and the third one further accounts for differences in educational progress by region (India) or region and race (South Africa, United States). The earnings of "treated" individuals are then reduced using estimates of the returns to schooling by level, as in the main analysis.

For India, the distribution of educational attainment by age, gender, and state of residence in 1983 is estimated using the 1983 National Sample Survey. The simulation is then run on the 2019 Periodic Labor Force Survey. For South Africa, educational attainment by age, gender, race, and province is estimated using the 2002 General Household Survey. The simulation is then run on the 2019 General Household Survey. For the United States, educational attainment by age, gender, state, and race is estimated using the 1980 Current Population Survey. The simulation is then run on the 2019 Current Population Survey.

Figure D2 plots schooling gains by income quintile, defined as the percent difference between actual income and counterfactual income absent educational expansion. As shown in the Figure, accounting for heterogeneous educational expansion by socioeconomic characteristic only marginally affects estimates of the aggregate and distributional effects of education.

D.5. Lost Income Due to School Attendance

If education had not improved, fewer young adults would be in school today. These individuals could be working instead of studying. In this section, I attempt to derive an upper bound on this opportunity cost. I consider an extreme scenario in which all individuals aged 15-25 currently attending school would instead be on the labor market if education had not improved. I assume that in this counterfactual, these individuals would face the same employment rate as other individuals in the same age group. The additional share of the adult population that would be employed in the counterfactual is:

$$\begin{aligned}\frac{\text{Newly Employed}}{\text{Adult Population}} &= \text{Share of Adults Aged 15-25} \\ &\quad \times \text{School Attendance Rate Among Adults Aged 15-25} \\ &\quad \times \text{Employment Rate Among Out-of-School Adults Aged 15-25}\end{aligned} \tag{D26}$$

In the average country, 26% of the adult population was aged 15-25 in 2019, and 44% of them were in school. Among those not in school, 55% were employed. This means that if all individuals aged 15-25 were to join the labor market instead of going to school, the share of the adult population in employment would increase by $0.26 \times 0.44 \times 0.55 = 0.06$. 6% of adults would thus start working.

I then assume that these additional workers would receive the same wage as workers aged 15-25 who are currently employed. Lost income as a share of total labor income is thus:

$$\frac{\text{Lost Income}}{\text{Total Labor Income}} = \frac{\text{Newly Employed}}{\text{Adult Population}} \times \frac{\text{Average Labor Income of Workers Aged 15-25}}{\text{Average Labor Income}} \tag{D27}$$

In the average country, the average income of workers aged 15-25 is about two-thirds of that of the overall adult population, so the opportunity cost of schooling amounts to about 4% of total labor income. To quantify the implications of this opportunity cost, I simply add this lost income to counterfactual incomes $y^p(A^{2019}, L^{1980})$ in each country. In other words, counterfactual income absent educational expansion would be higher in this scenario because of additional income generated by newly employed workers.

With these assumptions, I find that education accounts for 41% of global economic growth and 52% of growth among the world's poorest 20%. This should be seen as a very conservative lower bound, given that many young adults would still be in school today even if education had not improved since 1980.

D.6. Education Quality

Changes in education quality could affect the results of this paper. If education quality has increased or decreased, then educational attainment becomes a biased measure of actual changes in the education of the labor force: 1980 and 2019 levels of attainment are not comparable indicators anymore. In this section, I investigate available data on the evolution of education quality and implications for my analysis.

D.6.1. Trends in Education Quality: A Comparison of Available Estimates

International Test Scores Drawing from various international sources, Angrist et al. (2021) compile test score results for 163 countries over the 2000-2017 period, 122 of which have at least one data point in the 2000s and another data point in the 2010s. Figure D3a compares average test scores in the 2000s and 2010s for all countries with available data. Each data point corresponds to a test score in a given country, for a given education level (primary/secondary) and subject (mathematics/science/reading). All points are very close to the 45-degree line, suggesting that there has been little change in quality over the period. If anything, there has been a slight improvement in average quality: test scores have improved for 170 country-level-subject cells, while they have declined for 100.

For a more restricted number of countries, it is also possible to look at longer-run trends in education quality, based on the database compiled by Altinok, Angrist, and Patrinos (2018). Figure D3b plots the evolution of this indicator since 1970 for a selected number of high- and middle-income countries. The picture that arises is again one of remarkable stability, although some countries have undergone important long-run improvements, including Brazil, Chile, Iran, and South Korea.

Conditional Literacy Test scores suffer from a critical lack of historical depth for most countries in the world. To make a first step towards closing this gap, Le Nestour, Moscoviz, and Sandefur (2022) exploit information on literacy reported in the Demographic and Health Surveys and the Multiple Indicator Cluster Surveys. Based on this, Le Nestour, Moscoviz, and Sandefur (2022) exploit repeated cross-sections to identify changes in education quality by cohort, defined as expected literacy at grade 5. Figure D3c shows the main result of this exercise, comparing expected literacy for cohorts born in 1950-1960s versus 1980-2000. The estimates of Le Nestour, Moscoviz, and Sandefur (2022) point to a clear decline in quality in a number of developing countries.

These results are insightful, but it is important to stress that they do not necessarily imply that the results presented in this paper should be revised downwards for at least four reasons.

First, ability to read is a partial measure of quality. For instance, Hermo et al. (2022) show that the decline of vocabulary knowledge in Sweden since the 1960s has been accompanied by a significant increase in logical reasoning skills, which can be rationalized by increasing labor market returns to the latter. Second, identifying trends in the quality of education from repeated cross sections of surveys requires explicitly modeling age, period, and cohort effects, which makes the results more sensitive to methodological choices and measurement error. Third, such estimates are not immune to standard problems associated with causal identification (which is also true of test scores). Finally, changes in average performance may not necessarily imply lower returns to schooling. Even if newly educated cohorts may have lower levels of cognitive skills, economic returns to schooling for them may still be equal, or even greater (as suggested by the IV returns to schooling presented in the main text), than returns for the rest of the population. Put differently, differences in average skills may be very different from differences in marginal returns to skill.

Returns to Schooling Among U.S. Migrants A last piece of evidence comes from returns to schooling among U.S. migrants. Schoellman (2012) argues that differences in returns to schooling among U.S. migrants originating from different countries provides a good proxy for education quality, because it captures income gains from schooling for individuals having been educated in different countries but working in the same labor market. Schoellman (2012) provides evidence that this indicator is a good proxy for education quality, strongly correlating with GDP per capita and available test scores (see also Rossi, 2022).

I investigate trends in returns to schooling among U.S. migrants by pooling the 1980, 1990, and 2000 U.S. censuses, together with all American Community Surveys from 2001 to 2021. I restrict the sample to individuals aged 25 to 65 with positive earned income, who were born outside of the U.S. between 1950 and 1980, and arrived in the U.S. after age 20. I run the following regressions:

$$y_{icyt} = \zeta_{cy} s_{icyt} + X_{icyt}\beta_{cy} + \mu_t + \varepsilon_{icyt} \tag{D28}$$

With y_{icyt} the log of total annual earned income of individual i born in country c in decade y (1950s, 1960s, 1970s, or 1980s) and observed in year t. s_{icyt} is completed years of schooling, X_{icyt} are control variables (gender, state of residence, and year of immigration), and μ_t are census/ACS year fixed effects. The parameter of interest is ζ_{cy}, the return to a year of schooling for individuals born in country c in decade y. If education quality has declined substantially, then we should expect ζ_{cy} to have declined over time: a year of schooling should deliver greater returns for migrants born in the 1950s than for migrants born in the 1980s. I run this regression separately for each country of origin × decade of birth cell.

Figure D3d plots population-weighted averages of the estimated returns to schooling by world region of birth and decade of birth. Returns to schooling are lowest among migrants from Latin America and Sub-Saharan Africa and highest among migrants from Europe and the Anglosphere. There are fluctuations across decades, but no clear trend in quality in most regions. The world average varies from 7% to 9% with no clear trend.[5] This suggests again that changes in education quality are unlikely to play a substantial role in affecting the results presented in this paper.

D.6.2. A Quantification Exercise

While it remains unclear which data source should be preferred, it is still useful to test how sensitive my main findings are to accounting for the decline in quality documented in Le Nestour, Moscoviz, and Sandefur (2022). This is somewhat of a heroic task, because it requires (1) extrapolating cohort trends to cover education quality for the entire 1980-2019 working-age populations (2) putting a monetary value on literacy to build measures of quality-adjusted years of schooling, and (3) extrapolating changes in quality to

[5] Interestingly, the raw cross-country correlation between changes in these returns and changes in the Le Nestour, Moscoviz, and Sandefur (2022) indicator from the 1960s to 1980s cohorts is 0.33. This suggests that the two sources tell a broadly similar story on which countries have seen education quality decline or improve most.

countries with no available data. This section represents an exploratory attempt at doing so.

Methodological Framework Consider the standard extension of the Mincer-type human capital stock (e.g., Hanushek, Ruhose, and Woessman, 2017):

$$h = \exp(r_L L + r_Q Q) \tag{D29}$$

With r_L the return to a year of schooling, L average years of schooling, r_Q the return to education quality, and Q an indicator of education quality. The objective is to convert a change in quality from Q to $\tilde{Q}$ into an equivalent change in years of schooling from L to $\tilde{L}$. This equivalence satisfies:

$$\exp(r_L L + r_Q \tilde{Q}) = \exp(r_L \tilde{L} + r_Q Q) \tag{D30}$$

$$\Rightarrow \tilde{L} = L - \frac{r_Q}{r_L}(Q - \tilde{Q}) \tag{D31}$$

Calculating quality-adjusted years of schooling thus requires data on changes in quality $(Q - \tilde{Q})$ and the relative value of quality (r_Q) compared to quantity (r_L). I now turn to estimating each of these two components.

Estimation of Global Trends in Conditional Literacy The first step is to estimate $(Q - \tilde{Q})$, the evolution of quality of schooling for the working-age population from 1980 to 2019. The database of Le Nestour, Moscoviz, and Sandefur (2022) provides information on literacy at grade 5 in 86 countries for two cohorts born during the 1952-1999 period (see Le Nestour, Moscoviz, and Sandefur, 2022, Table 7). Starting from these two data points by country, I estimate average conditional literacy for the working-age population.

First, I divide all figures by 5, so that the indicator corresponds to expected literacy per year of education. Second, I linearly interpolate and extrapolate this indicator backwards and forwards, to cover all cohorts born from 1915 to 1994. This is a very conservative assumption: it amounts to considering that education quality continued to decline at the same pace after the last cohort observed, and was already declining at the same pace from 1915 until the first cohort observed. Third, I construct measures of average education quality of the working-age population by averaging the indicator over all cohorts aged 25 to 65 in a given year, weighted by the population of each cohort. Data on population by age is taken from the United Nations' World Population Prospects. Finally, I impute the indicator for missing countries. To be as conservative as possible, I assume that quality in missing countries has declined at the speed of India, that is, at a very fast pace. I view this last case as an extreme and implausible scenario, given above-mentioned evidence on the stability or rise of test scores in many countries.

Estimation of Returns to Literacy The second step is to estimate r_Q/r_L, the return to literacy relative to a year of schooling. This requires data on personal income, years of schooling, and literacy at the individual level. I was able to find four high-quality surveys covering these three variables: the Brazilian 2015 PNAD survey, the Indonesian 1998 SUSENAS survey, the Pakistani 2018 HIES survey, and the South African 2019 GHS survey. In each of these four countries, I estimate the relative returns to literacy by running two regressions: a regression relating the log of total personal income to literacy, and a regression relating the log of total personal income to years of schooling, controlling for gender, age, and age squared in each case. I restrict the sample to workers with either no schooling or basic education, to make sure that the two estimates are comparable (nearly all workers with more than basic education are literate).

The results are presented in Table D6. Returns to schooling range from 3% to 6% per year of basic education, while returns to literacy range from 16 to 34 log points. The ratio between the two coefficients is very similar across countries, ranging from 5 in Pakistan to 7 in Indonesia. I take a value of 6 in what follows. This amounts to assuming that moving the entire population from being illiterate to literate is equivalent to increasing average schooling by 6 years.

Results Finally, I construct measures of quality-adjusted years of schooling. I set 1980 as the benchmark year, and adjust estimates of average years of schooling in all other years from 1981 to 2019 so that they reflect the quality observed in 1980. For instance, quality-adjusted years of schooling in 2019 are calculated as $\tilde{L}_{2019} = L_{2019} - \frac{r_Q}{r_L}(Q_{2019} - Q_{1980})$, with L_{2019} unadjusted years of schooling observed in 2019, $\frac{r_Q}{r_L} = 6$, and $Q_{2019} - Q_{1980}$ the change in expected literacy per year of schooling from 1980 to 2019. This approach thus amounts to "deflating" years of schooling observed from 1981 to 2019 to express them in 1980 equivalents.

Figure D4 compares the share of growth explained by global income percentile before and after making this adjustment. The two lines are very close to each other: even under the very conservative assumptions on the decline in education quality outlined above, the main results are almost unchanged. The share of growth explained by education declines by about 2 to 10 percentage points depending on the percentile considered, with the greatest changes observed at the upper-middle of the distribution. The results presented in this paper thus appear to be strongly robust to potential changes in education quality observed since 1980.

Table D1 – IV Estimates of the Returns to Schooling

Source	Country	Policy	Level	Gender	OLS β	IV β	OLS SE	IV SE
Selected Studies								
Leigh and Ryan (2008)	Australia	CSL	Secondary	A	12.8	11.8	.5	3.5
Lemieux and Card (2001)	Canada	EXP	Tertiary	A	7	8	.2	4.4
Oreopoulos (2006b)	Canada	CSL	Secondary	A	9.9	9.6	.7	2.5
Fang et al. (2012)	China	CSL	Secondary	A	9	20	.4	.6
Huang and Zhu (2022)	China	EXP	Tertiary	M	4.9	16.5	.2	2.8
Assaad et al. (2023)	Egypt	CSL	Primary	A	2.1	3.8	.3	4.5
Brunello, Weber, and Weiss (2015)	Europe	CSL	Secondary	A	4.2	5.6	.3	2.6
Khanna (2023)	India	EXP	Primary	A	10	15.5		
Carneiro, Lokshin, and Umapathi (2017)	Indonesia	EXP	Secondary	A	9	12.9	.5	4.8
Duflo (2001)	Indonesia	EXP	Primary	A	7.7	10.6	.06	2.2
Denny and Harmon (2000)	Ireland	EXP	Secondary	A	7.9	13.6	.6	2.5
Kuwait (2024)	Kuwait	EXP	Secondary	M	8.6	5	.03	.2
Fabregas and Navarro-Sola (2024)	Mexico	EXP	Secondary	A	19	19		
Oyelere (2010)	Nigeria	EXP	Primary	A	2.6	2.7	.1	1.3
Aakvik, Salvanes, and Vaage (2010)	Norway	CSL	Secondary	M	8.2	9.4	.1	.2
Bhuller, Mogstad, and Salvanes (2017)	Norway	CSL	Secondary	A	9.3	11.2	.2	4.8
Sakellariou (2006)	Philippines	EXP	Secondary	M	6.1	11.4		
Portugal et al. (forthcoming)	Portugal	CSL	Secondary	A	8.54	9.34	.01	.06
Vieira (1999)	Portugal	CSL	Primary	A	7.8	5.3		
Kyui (2016)	Russian Federation	EXP	Tertiary	A	5.5	16.1	.2	1
Meghir and Palme (1999)	Sweden	CSL	Secondary	A	2.8	3.6	.7	2.1
Spohr (2003)	Taiwan	CSL	Secondary	M	5.4	5.8	.01	2.6
Zhang (2020)	Taiwan	CSL	Secondary	A	6.7	5.6	.01	.1
Delesalle (2021)	Tanzania	EXP	Primary	A	2.6	5.7	.01	2.1
Korwatanasakul (2023)	Thailand	CSL	Primary	A	10.9	7.64	.17	.75

Patrinos, Psacharopoulos, and Tansel (2020)	Turkey	CSL	Primary	M	8.3	18		
Torun (2018)	Turkey	CSL	Primary	M	2.4	1.7	1	1
Clay, Lingwall, and Stephens (2021)	USA	CSL	Secondary	M	8.4	7.7	.1	1.5
Li (2024)	USA	CSL	Secondary	W	11.2	16.9	.1	2.3
Stephens and Yang (2014)	USA	CSL	Secondary	A	6.3	-1.4		
Zimmerman (2014)	USA	THR	Tertiary	A	10	14		
Patrinos and Sakellariou (2005)	Venezuela	CSL	Secondary	A	5.2	8.6		
Vu and Vu-Thanh (2022)	Viet Nam	EXP	Tertiary	A	11.2	19		
Other Studies								
Alzúa, Gasparini, and Haimovich (2015)	Argentina	CSL	Secondary	A		15.8		4.2
Powdthavee, Lekfuangfu, and Wooden (2013)	Australia	CSL	Secondary	M		15.5		3.3
Eble and Hu (2019)	China	CSL	Primary	A		5.2		
Fan et al. (2018)	China	THR	Tertiary	A		6.6		3.2
Brunello, Fort, and Weber (2009)	Europe	CSL	Secondary	M		5.1		
Hsiao (2023)	Indonesia	EXP	Primary	A		26		
Hicks and Duan (2023)	Jordan	CSL	Secondary	A		5.2		
Liwiński (2020)	Poland	CSL	Secondary	A		13.1		4.7
Fischer et al. (2019)	Sweden	CSL	Primary	A		2.4		.6
Meghir and Palme (2005)	Sweden	CSL	Secondary	A		4.8		
Aydemir and Kirdar (2017)	Turkey	CSL	Secondary	M		2.5		
Oreopoulos and Salvanes (2011)	USA	CSL	Secondary	M		13.1		.6
Excluded Studies								
Filmer and Schady (2014)	Cambodia	THR	Secondary	A		20.8		340.8
Domnisoru (2021)	France	CSL	Secondary	M		5.4		1.7
Grenet (2013)	France	CSL	Secondary	M	7.3	-.4	.1	2.9
Pischke (2007)	Germany	CSL	Secondary	A				
Pischke and Wachter (2008)	Germany	CSL	Secondary	A	7.4	1.6	.1	1.5
Duflo, Dupas, and Kremer (2024)	Ghana	EXP	Secondary	A				

Oosterbeek and Webbink (2007)	Netherlands	CSL	Secondary	A				
Buscha and Dickson (2012)	United Kingdom	CSL	Secondary	A		7.1		9.2
Buscha and Dickson (2015)	United Kingdom	CSL	Secondary	A		7		
Clark (2023)	United Kingdom	CSL	Secondary	A		.01		2.3
Delaney and Devereux (2019)	United Kingdom	CSL	Secondary	A		6		
Devereux and Hart (2010)	United Kingdom	CSL	Secondary	A		3		
Dickson (2013)	United Kingdom	CSL	Secondary	A	4.6	10.2	.3	5.1
Dolton and Sandi (2017)	United Kingdom	CSL	Secondary	M		6		
Grenet (2013)	United Kingdom	CSL	Secondary	M	9.5	6.9	.1	2.9
Harmon and Walker (1995)	United Kingdom	CSL	Secondary	A	6.1	15.3	.1	1.5
Oreopoulos (2006a)	United Kingdom	CSL	Secondary	A	8.3	14.8	.1	4.6

Notes. The table reports OLS and IV estimates of the returns ot schooling from a collection of existing studies. Policy: IV return to schooling derived from the analysis of compulsory schooling laws (CSL), other educational expansion policies (EXP), or college admission thresholds (THR). Gender: return to schooling estimated in a sample of both men and women (A), men only (M), or women only (W). OLS/IV β: OLS/IV return per year of education. OLS/IV SE: OLS/IV coefficient standard error.

Table D2 – Empirical Estimates of the Elasticity of Substitution Between Skill Groups

Source	Country	Tertiary/Below	Secondary/Below
Long-run elasticity			
Bils, Kaymak, and Wu (2022)	Cross-Country	4 to 6	4 to 6
Hendricks and Schoellman (2023)	Cross-Country	4.5	7.8
Short-run elasticity			
Bowlus et al. (2021)	United States	5.3	
Autor, Goldin, and Katz (2020)	United States	1.62	
Hershbein, Kearney, and Pardue (2020)	United States	1.4	
Acemoglu and Autor (2011)	United States	1.6	
Goldin and Katz (2007)	United States	1.6	2 to 5
Ciccone and Peri (2005)	United States	1.5	
Heckman, Lochner, and Taber (1998)	United States	1.4	
Katz and Murphy (1992)	United States	1.41	
Murphy, Riddell, and Romer (1998)	Canada	1.36	
Angrist (1995)	Palestine	2	
Vu and Vu-Thanh (2022)	Vietnam	2.67	
Fernández and Messina (2018)	Latin America	1.25	2.3
Khanna (2023)	India		4.24
Caselli and Coleman (2006)	Cross-Country	1.3	

Notes. The table reports selected estimates of the elasticity of substitution between skill groups from various empirical studies. Bils, Kaymak, and Wu (2022): unique elasticity of substitution for all skill groups. Khanna (2023): primary/below.

Table D3 – Distributional Growth Accounting, World, 1980-2019:
With Physical Capital Affected by Education

	Annual Income Growth (%)	Contribution of Education (pp.)	Share of Growth Explained (%)
Full Population	1.6%	1.0	62%
Bottom 50%	2.4%	1.3	51%
Bottom 20%	1.9%	1.3	67%
Next 30%	2.6%	1.2	49%
Middle 40%	1.5%	1.3	84%
Top 10%	1.6%	0.8	50%
Top 1%	2.0%	0.7	32%
Top 0.1%	2.5%	0.7	26%

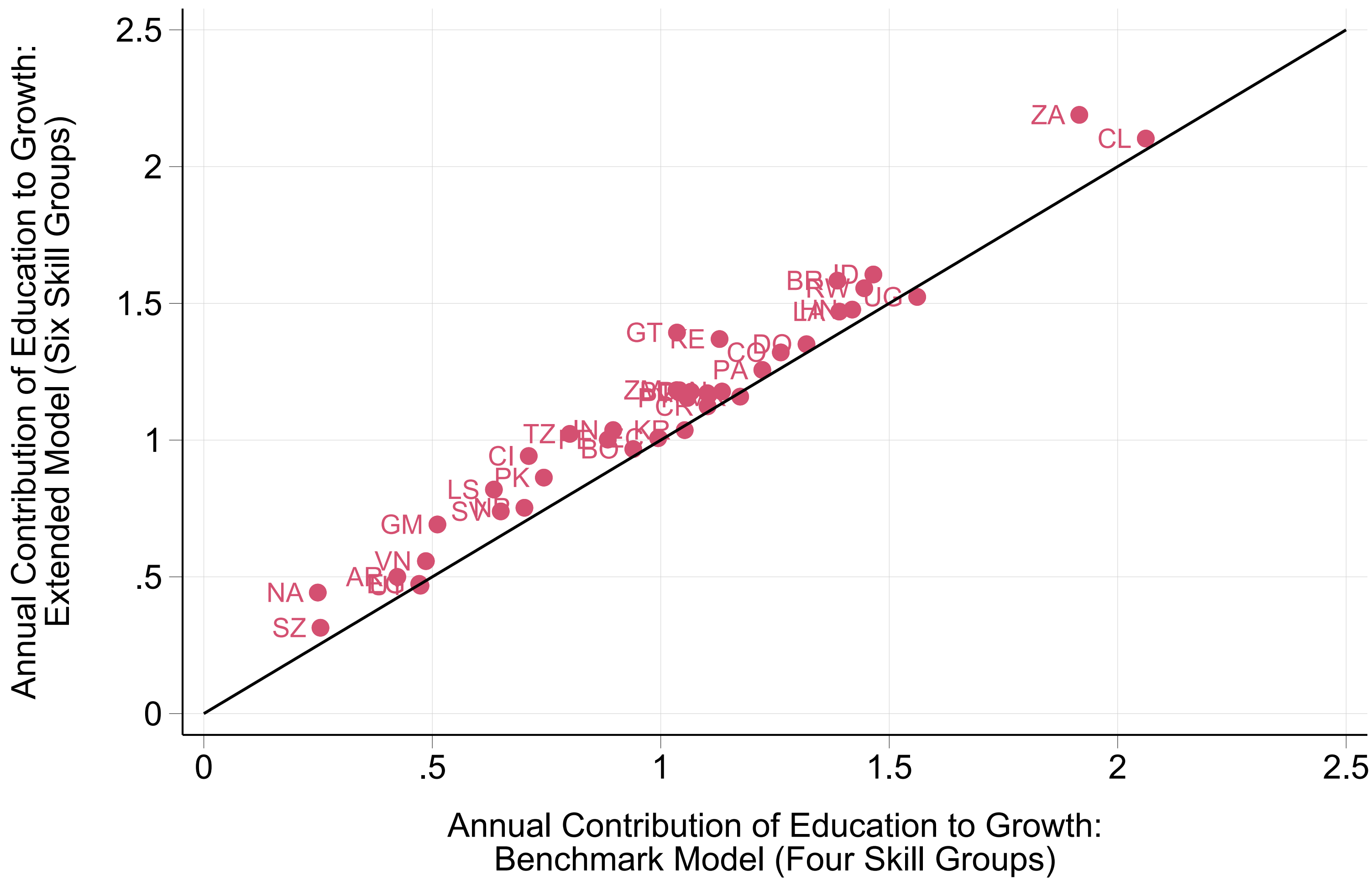
Notes. The table reports actual real annual income growth rates, the contribution of education to growth, and the corresponding share of growth explained by education for different groups of the world distribution of income. Physical capital is assumed to adjust in the counterfactual so as to keep the capital-to-output ratio constant in each country.

Table D4 – Complete Growth Decomposition by World Region, 1980-2019

	Actual Growth	Education	Physical Capital	Residual
Average Country	3.1%	0.7%	1.2%	1.1%
Europe / Northern America	1.6%	0.8%	0.4%	0.4%
Latin America	0.6%	0.8%	0.5%	-0.7%
China	6.1%	0.8%	2.7%	2.6%
India	4.0%	0.6%	1.5%	1.9%
Other Asia-Pacific	3.0%	0.7%	1.1%	1.2%
Middle East and North Africa	1.8%	0.5%	1.5%	-0.2%
Sub-Saharan Africa	1.0%	0.8%	0.1%	0.1%

Notes. The table decomposes average annual income growth into the total contribution of education, the contribution of physical capital, and residual growth by world region. Population-weighted averages of growth rates and contributions of education and physical capital in each country.

Figure D1 – Accounting for Within-Category Variations in Human Capital
Benchmark versus Extended Model with Six Skill Groups: Contribution of Education to Growth



Notes. The table compares the annual contribution of education to economic growth estimated when using the benchmark model versus an extended model with six skill groups, distinguishing workers with incomplete versus complete primary and secondary education. The contribution of education to annual real income growth is equal to the annualized log difference between actual and counterfactual human capital in each country: $\frac{1}{39} \times (\ln H(A^{2019}, L^{2019}) - \ln H(A^{2019}, L^{1980}))$.

Table D5 – Accounting for Within-Category Variations in Human Capital
Benchmark versus Extended Model with Six Skill Groups: Results by Country

	Returns to Schooling		Contribution of Education to Annual Growth (pp.)		Share of Growth Explained by Education (%)	
	Complete Primary	Complete Secondary	Benchmark Model	Extended Model	Benchmark Model	Extended Model
Average Country	14%	27%	1.0	1.1	39%	43%
Argentina	19%	26%	0.4	0.5	61%	72%
Bangladesh	9%	36%	1.1	1.2	22%	24%
Bolivia	31%	3%	0.9	1.0	46%	47%
Brazil	35%	22%	1.4	1.6	>100%	>100%
Chile	8%	19%	2.1	2.1	49%	50%
China	21%	32%	1.1	1.2	14%	14%
Colombia	20%	34%	1.3	1.3	53%	55%
Costa Rica	20%	28%	1.1	1.1	36%	37%
Cote d'Ivoire	17%	71%	0.7	0.9	58%	77%
Dominican Republic	19%	8%	1.3	1.4	27%	27%
Ecuador	30%	17%	1.0	1.0	94%	95%
Egypt	2%	0%	0.5	0.5	8%	8%
El Salvador	31%	17%	0.6	0.7	49%	55%
Eswatini	19%	85%	0.3	0.3	12%	14%
Gambia	14%	23%	0.5	0.7	>100%	>100%
Guatemala	32%	59%	1.0	1.4	>100%	>100%
Honduras	52%	48%	1.4	1.5	>100%	>100%
India	3%	19%	0.9	1.0	14%	17%
Indonesia	17%	35%	1.5	1.6	28%	31%
Kenya	37%	45%	1.1	1.4	>100%	>100%
Lao	7%	11%	1.4	1.5	18%	19%
Lesotho	13%	51%	0.6	0.8	33%	42%
Mexico	30%	28%	1.2	1.2	>100%	>100%
Namibia	25%	92%	0.2	0.4	28%	50%
Nepal	4%	10%	0.7	0.8	19%	20%
Pakistan	3%	32%	0.7	0.9	26%	30%
Panama	29%	37%	1.2	1.3	23%	24%
Paraguay	19%	23%	1.1	1.2	44%	48%
Peru	9%	15%	0.9	1.0	39%	45%
Rwanda	22%	31%	1.4	1.6	49%	53%
South Africa	13%	42%	1.9	2.2	>100%	>100%
South Korea	10%	18%	1.1	1.0	15%	15%
Tanzania	24%	73%	0.8	1.0	32%	41%
Thailand	19%	16%	1.1	1.2	19%	20%
Uganda	23%	104%	1.6	1.5	45%	44%
Uruguay	29%	29%	0.5	0.5	15%	15%
Vietnam	9%	29%	0.5	0.6	7%	8%
Zambia	21%	55%	1.0	1.2	>100%	>100%

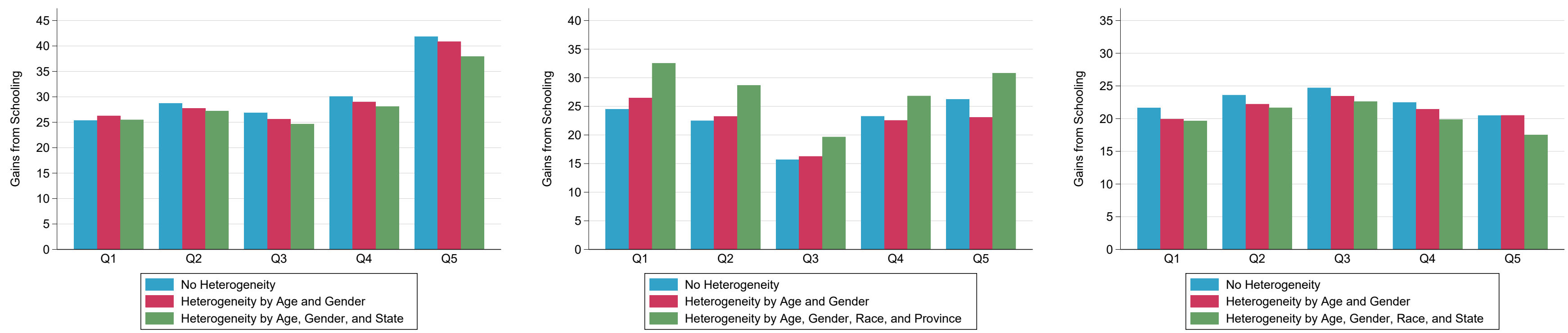
Notes. The table compares growth accounting results obtained when using the benchmark model versus an extended model with six skill groups, distinguishing workers with incomplete versus complete primary and secondary education. Returns to schooling: estimated returns to complete relative to incomplete primary education, and to complete relative to incomplete secondary education. Contribution of education to annual growth: $\frac{1}{39} \times (\ln H(A^{2019}, L^{2019}) - \ln H(A^{2019}, L^{1980}))$.

Figure D2 – Accounting for Heterogeneous Educational Expansion: Gains from Schooling With and Without Heterogeneous Educational Expansion by Socioeconomic Characteristic

(a) India, 1983-2019

(b) South Africa, 2002-2019

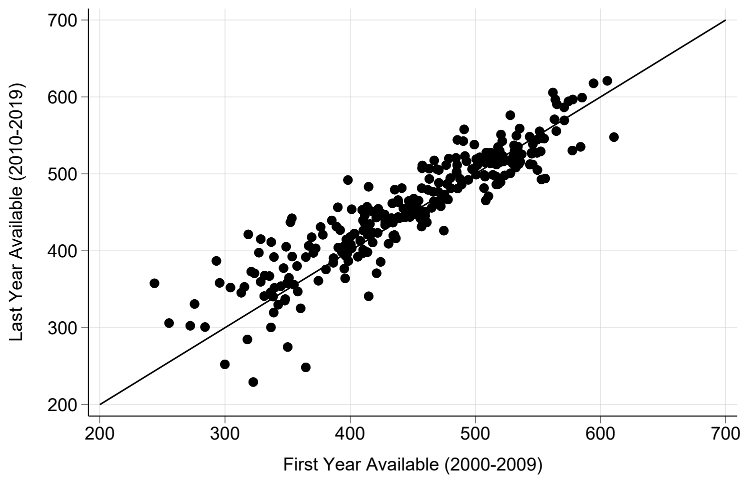
(c) United States, 1980-2019



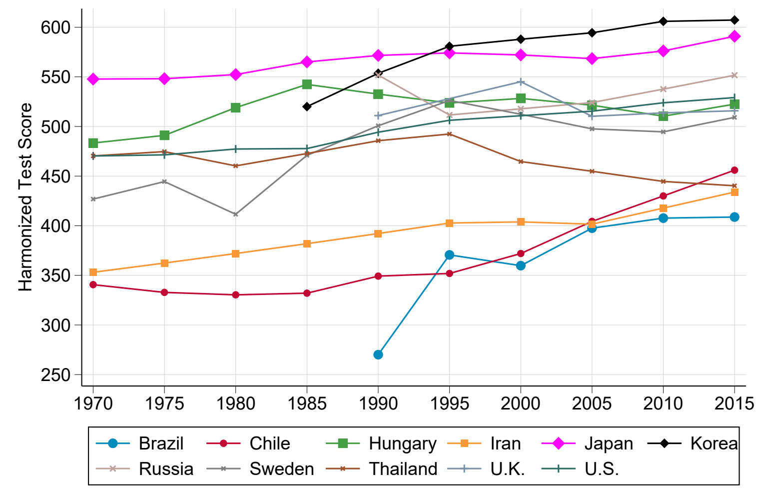
Notes. The figure compares gains from education by income quintile before and after accounting for heterogeneous educational expansion by socioeconomic characteristic in India, South Africa, and the United States. In each case, education levels of individuals are downgraded without any heterogeneity (specification 1), by age-gender cell (specification 2), or by age-gender-region-race or age-gender-region cell (specification 3) until reaching counterfactual levels. Their earnings are then reduced using estimates of returns to schooling by level. Finally, the figure plots schooling gains by income quintile, defined as the percent difference between actual income and counterfactual income absent educational expansion. India: educational attainment by age, gender, and state of residence in 1983 estimated using the 1983 National Sample Survey; simulation run on the 2019 Periodic Labor Force Survey. South Africa: educational attainment by age, gender, race, and province estimated using the 2002 General Household Survey; simulation run on the 2019 General Household Survey. United States: educational attainment by age, gender, state, and race estimated using the 1980 Current Population Survey; simulation run on the 2019 Current Population Survey.

Figure D3 – Accounting for Education Quality: Empirical Evidence on the Evolution of Education Quality

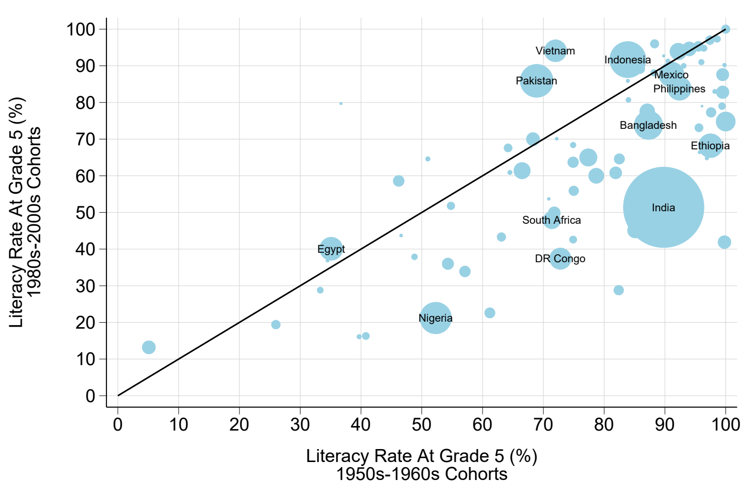
(a) Harmonized Test Scores: 2000-2009 vs. 2010-2019



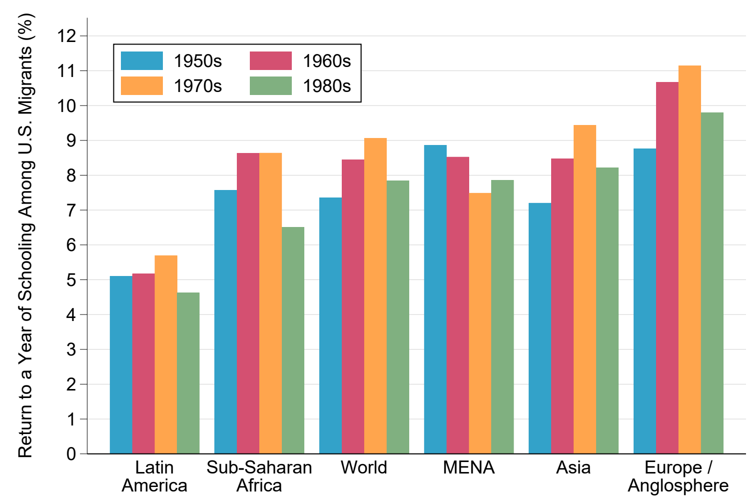
(b) Long-Run Trends in Test Scores in Selected Countries



(c) Literacy at Grade 5: 1950-1960 versus 1980-2000 Cohorts



(d) Trends in Returns to Schooling Across Cohorts of U.S. Migrants



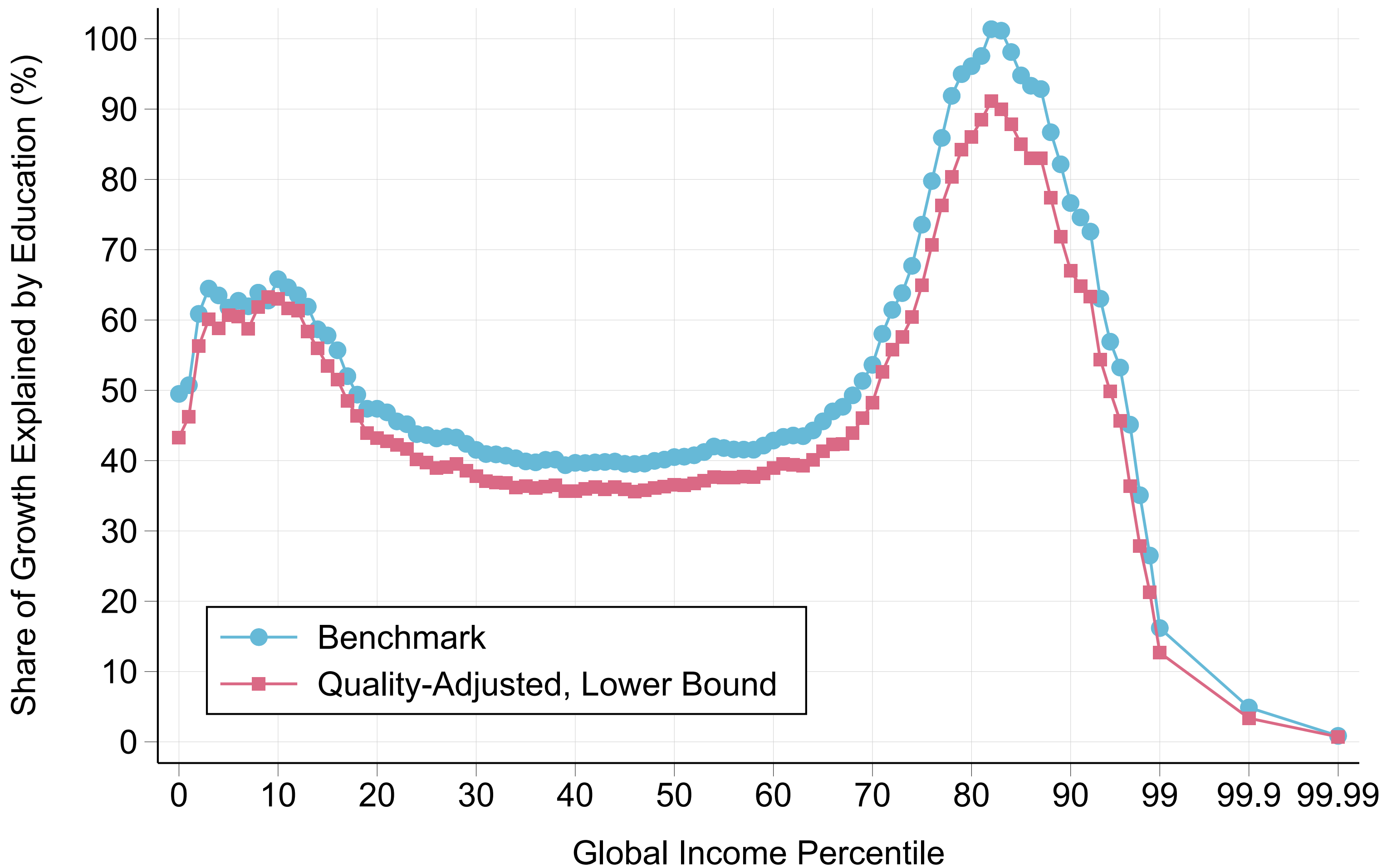
Notes. The figure provides empirical evidence on the evolution of education quality from various data sources. Panel (a) compares average test scores in 2000-2009 and 2010-2019 based on data from Angrist et al. (2021). Each point corresponds to a test score reported for a given country × education level (primary/secondary) × subject (maths/science/reading). Panel (b) plots the evolution of harmonized test scores in selected countries from 1970 to 2015, based on data from Altinok, Angrist, and Patrinos (2018). Panel (c) compares expected literacy at age 5 among 1950s-1960s cohorts (x-axis) and 1980s-2000s cohorts (y-axis), drawing on estimates from Le Nestour, Moscoviz, and Sandefur (2022). Panel (d) plots the return to a year of schooling among U.S. migrants coming from each world region, based on data from U.S. censuses and American Community Surveys. Population-weighted average of returns to schooling estimated for a given country of origin × decade of birth cell.

Table D6 – Accounting for Education Quality:
Returns to Literacy

	Brazil	Indonesia	Pakistan	South Africa
Return to Literacy	0.34***	0.34***	0.26***	0.16***
	(0.01)	(0.01)	(0.01)	(0.05)
Return to Schooling	0.06***	0.05***	0.05***	0.03***
	(0.00)	(0.00)	(0.00)	(0.01)
Literacy / Schooling	5.75	7.38	5.31	6.48

Notes. The table reports estimates of returns to literacy, returns to schooling, and the ratio between the two. The coefficient on literacy corresponds to a regression of the log of personal income on literacy; the coefficient on years of schooling corresponds to a separate regression of the log of personal income on years of schooling. Both regressions control for gender, age, and age squared in each country. Data sources: 2015 Brazil PNAD survey, 1998 Indonesia SUSENAS survey, 2018 Pakistan HIES survey, 2019 South Africa GHS survey. Standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure D4 – Accounting for Education Quality:
Share of Growth Explained by Education: Benchmark Versus Lower Bound on Decline in Education Quality



Notes. The figure plots the share of growth explained by education by global income percentile, before and after adjusting educational attainment for potential changes in education quality. Quality-adjusted estimates correct years of schooling for the decline in education quality estimated by Le Nestour, Moscoviz, and Sandefur (2022), so that years of schooling are expressed in 1980 equivalents throughout the period. Countries with missing data are attributed the decline in quality observed in India.

E. Data Appendix: Survey Microdata

E.1. Main Survey Microdatabase

The survey microdata used in the main analysis come from five main data sources. Table E1 reports the names and years of surveys used in each country.

ILO Microdata The main data source is a set of harmonized household surveys that were collected and compiled by the International Labor Organization. These surveys were run by statistical institutes and are nationally representative. The majority of them are labor force surveys explicitly designed to measure labor market variables. Other surveys are typically household income and expenditure surveys, or multi-purpose surveys that collected information on a range of indicators together with labor market variables. I use the survey closest to 2019 in each country. The database presents itself as a single harmonized microfile. The main variables are country, year, household ID, sample weight, wage income (from main job, second job, and all jobs combined), self-employment income (from main job, second job, and all jobs combined), age, gender, education, labor force participation, occupation (ISCCO-08), industry, and rural-urban location. I define personal income as the sum of all wage and self-employment income received by an individual. The sample is restricted to all individuals with strictly positive personal income.

European Statistics on Income and Living Conditions Although the ILO data do cover European countries, the coding of educational attainment is broader than in the original microfiles, so I decide to rely on my own data collection. The European Statistics on Income and Living Conditions (EU-SILC) cover detailed information on personal income and education in 32 countries from 2003 to 2020. I harmonize EU-SILC surveys in the same way as those of the ILO, defining personal income as the sum of individual wage and mixed income. I then replace all ILO surveys by this microfile, with the exception of France, Portugal, and Switzerland, for which the ILO provides national labor force surveys of even better quality.

I2D2 Database The I2D2 database consists in a set of harmonized surveys that have been compiled by the World Bank since the 1990s. Many surveys are common to the ILO and I2D2 database, but they differ in two dimensions. First, the ILO prioritizes labor force surveys, while the I2D2 database is more focused on household income and expenditure surveys. Second, the ILO microdata has better coverage of recent years (the I2D2 was discontinued in 2017), while the I2D2 database has better historical coverage. In the main analysis, I use the I2D2 to cover 11 additional countries that are not in the ILO database: Azerbaijan, Gabon, Georgia, Haiti, Iran, Kyrgyzstan, Kosovo, Kazakhstan, North Macedonia, Saudi Arabia, and Ukraine.

Life in Transition Survey For Belarus, Montenegro, Uzbekistan, I rely on the Life in Transition Survey (LITS). The LITS is far from being ideal, with sample sizes of only 3,000-5,000, yet it is to the best of my knowledge the only data source available to measure individual incomes and education in these three countries. I use the last wave of the LITS, fielded in 2016, which I harmonize in the same way as the ILO.

Country-Specific Surveys Finally, I collect and harmonize surveys from country-specific data portals to cover 11 additional countries: China, Iraq, India, Japan, Mozambique, Morocco, Russia, Somalia, South Africa, South Korea, South Sudan, Tunisia, and the United States.

For seven countries, I was available to find and harmonize a high-quality survey providing detailed information on individual incomes. This type of survey was available for China (2018 Chinese Household Income Project), India (2019 Periodic Labor Force Survey), Russia (2019 Russia Longitudinal Monitoring Survey), South Korea (2019 Korean Labor and Income Panel Study), Tunisia (2014 Labor Force Survey), South Africa (2019 General Household Survey), and the United States (2019 Current Population Survey).

For six other countries, I rely on surveys of lower quality or only providing information on household expenditure. For Japan, in the absence of better publicly available data, I use the 2017 general household survey, which does cover individual income and education but has a small sample size (about 1,000). I use household income and expenditure surveys for Iraq (Household Socio-Economic Survey), Mozambique (Inquérito aos orcamentos familiares), Morocco (Household Expenditure Survey), Somalia (High Frequency Survey), and South Sudan (High Frequency Survey), which provide information on individual employment and education, as well as total household expenditure, but not on individual incomes. In the absence of better information, I proxy personal income by splitting equally household expenditure among adults in employment, excluding unemployed or inactive individuals as well as children.

Data Quality The surveys used in each country vary in their focus and sample size, which makes them a more or less ideal source to measure the relationship between education and individual incomes. In Table E1, I classify the quality of each survey as high, medium, or low. High-quality surveys are surveys with detailed labor and individual income modules and large sample sizes (102 countries representing 61% of the world's population). Medium-quality surveys are multi-purpose surveys that collected information on both labor market variables and other dimensions of households' economic conditions (43 countries, 32% of the world's population). Low-quality surveys are surveys with low sample sizes and/or no information on personal income (9 countries, 4% of the world's population).

E.2. Historical Survey Microdatabase

In section V, I estimate skill-biased technical change since 2000 in 109 countries. The surveys used in this part of the analysis come from four main sources.

The primary source is the I2D2 database, which allows me to cover the distribution of education and income in 63 countries around 2000.

The second source is the Global Labor Database maintained by the World Bank, which is similar to I2D2 but specifically focused on labor force surveys. It allows me to cover 11 additional countries: Brazil, Chile, Colombia, Indonesia, India, Mongolia, Nepal, the Philippines, Pakistan, Thailand, and Turkey. I also rely on the Global Monitoring Database, the successor of the I2D2, to cover Bhutan, and on the ILO microdatabase to cover Canada and Cambodia.

The third source is EU-SILC, which allows me to cover 29 European countries. While EU-SILC was first fielded in 2003, personal income and educational attainment suffer from measurement problems in the earlier waves of the survey, so I use the 2006 wave. Unfortunately, this is the only survey available when it comes to accurately measuring incomes and education in the European Union in the 2000s.

Finally, I rely on country-specific surveys for China (2002 Chinese Household Income Project), Russia (2000 Russia Longitudinal Monitoring Survey), and the United States (2000 Current Population Survey).

The complete list of surveys is reported in Table E2, together with a quality indicator derived in the same way as in Table E1.

Table E1 – Survey Data Sources: Main Analysis

Country	Source	Survey Year	Quality
Europe			
Albania	Living Standards Survey	2012	Medium
Austria	EU Statistics on Income and Living Conditions	2019	High
Belarus	Life in Transition Survey	2016	Low
Belgium	EU Statistics on Income and Living Conditions	2019	High
Bosnia and Herzegovina	Labour Force Survey	2016	High
Bulgaria	EU Statistics on Income and Living Conditions	2019	High
Croatia	EU Statistics on Income and Living Conditions	2019	High
Czechia	EU Statistics on Income and Living Conditions	2019	High
Denmark	EU Statistics on Income and Living Conditions	2019	High
Estonia	EU Statistics on Income and Living Conditions	2019	High
Finland	EU Statistics on Income and Living Conditions	2019	High
France	Employment Survey	2019	High
Germany	EU Statistics on Income and Living Conditions	2019	High
Greece	EU Statistics on Income and Living Conditions	2019	High
Hungary	EU Statistics on Income and Living Conditions	2019	High
Iceland	EU Statistics on Income and Living Conditions	2018	High
Ireland	EU Statistics on Income and Living Conditions	2019	High
Italy	Labour Force Survey	2019	High
Latvia	EU Statistics on Income and Living Conditions	2019	High
Lithuania	EU Statistics on Income and Living Conditions	2019	High
Luxembourg	EU Statistics on Income and Living Conditions	2019	High
Malta	EU Statistics on Income and Living Conditions	2019	High
Moldova	Labour Force Survey	2019	High
Montenegro	Life in Transition Survey	2016	Low
Netherlands	EU Statistics on Income and Living Conditions	2019	High
North Macedonia	Labor Force Survey	2019	High
Norway	EU Statistics on Income and Living Conditions	2019	High
Poland	EU Statistics on Income and Living Conditions	2019	High
Portugal	Employment Survey	2019	High
Romania	EU Statistics on Income and Living Conditions	2019	High
Russia	Russia Longitudinal Monitoring Survey	2019	Medium
Serbia	Labour Force Survey	2019	High
Slovakia	EU Statistics on Income and Living Conditions	2019	High
Slovenia	EU Statistics on Income and Living Conditions	2019	High
Spain	EU Statistics on Income and Living Conditions	2019	High
Sweden	EU Statistics on Income and Living Conditions	2019	High
Switzerland	Labour Force Survey	2019	High
Ukraine	Household Living Conditions Survey	2019	Medium
United Kingdom	Labour Force Survey	2018	High
Northern America			
Canada	Labour Force Survey	2019	High
USA	Current Population Survey	2019	High
Latin America			
Argentina	Permanent Household Survey, Urban	2019	Medium
Barbados	Survey on Living Conditions	2016	Medium
Belize	Labour Force Survey	2019	High
Bolivia	Continuous Employment Survey	2019	High
Brazil	Continuous National Household Sample Survey	2019	High
Chile	National Survey on Socio-Economic Conditions	2017	High
Colombia	Integrated Household Survey	2019	High
Costa Rica	National Household Survey	2019	Medium
Dominican Republic	Continuous National Labour Force Survey	2019	High
Ecuador	National Survey on Employment	2019	High
El Salvador	Multi-purpose Household Survey	2019	Medium
Guatemala	Monthly Employment and Income Survey	2019	High
Guyana	Labour Force Survey	2019	High
Haiti	Enquête sur les Conditions de Vie des Ménages	2012	Medium

Honduras	Continous Multi-Purpose Household Survey	2019	Medium
Jamaica	Labour Force Survey	2014	High
Mexico	National Occupation and Employment Survey	2019	High
Nicaragua	National Household Survey on Measuring Living Conditions	2014	Medium
Panama	Labour Market Survey	2019	High
Paraguay	Continous Household Survey	2017	High
Peru	National Household Survey	2019	Medium
Suriname	Survey on Living Conditions	2016	Medium
Trinidad and Tobago	Continuous Sample Survey of the Population	2016	Medium
Uruguay	Continous Household Survey	2019	Medium
Venezuela	Household Sample Survey	2017	Medium
Asia			
Afghanistan	Households Living Conditions Survey	2014	Medium
Australia	Household, Income and Labour Dynamics Survey	2019	High
Bangladesh	Labour Force Survey	2017	High
Bhutan	Labour Force Survey	2019	High
Brunei Darussalam	Labour Force Survey	2014	High
Cambodia	Labour Force Survey	2019	High
China	China Household Income Project	2018	Medium
Fiji	Employment, Unemployment Survey	2016	High
India	Periodic Labour Force Survey	2019	High
Indonesia	National Labour Force Survey	2019	High
Iran	Household Expenditure and Income Survey	2019	Medium
Japan	General Social Survey	2017	Low
Kazakhstan	Household Budget Survey	2017	Medium
Kosovo	Labor Force Survey	2017	High
Kyrgyzstan	Kyrgyz Integrated Household Survey	2017	Medium
Lao	Labour Force Survey	2017	High
Maldives	Household Income and Expenditure Survey	2019	Medium
Mongolia	Labour Force Survey	2019	High
Myanmar	Labour Force Survey	2019	High
Nepal	Labour Force Survey	2017	High
Pakistan	Labour Force Survey	2019	High
Philippines	Labour Force Survey	2018	High
South Korea	Korean Labor and Income Panel Study	2019	High
Sri Lanka	Labour Force Survey	2018	High
Tajikistan	Living Standards Survey	2009	Medium
Thailand	Household Socio-Economic Survey	2019	Medium
Timor-Leste	Labour Force Survey	2016	High
Tonga	Labour Force Survey	2018	High
Uzbekistan	Life in Transition Survey	2016	Low
Vietnam	Labour Force Survey	2019	High
Middle East and North Africa			
Armenia	Household Labour Force Survey	2019	High
Azerbaijan	Monitoring Survey for Social Welfare	2015	Medium
Cyprus	EU Statistics on Income and Living Conditions	2019	High
Egypt	Labour Force Sample Survey	2018	High
Georgia	Household Integrated Survey	2019	Medium
Iraq	Household Socio-Economic Survey	2012	Low
Jordan	Employment and Unemployment Survey	2019	High
Lebanon	Labour Force Survey	2019	High
Morocco	Household Expenditure Survey	2014	Low
Palestine	Labour Force Survey	2019	High
Saudi Arabia	Household Expenditure and Income Survey	2013	Medium
Sudan	Household Survey	2011	Medium
Tunisia	Labor Force Survey	2014	High
Turkey	Household Labour Force Survey	2019	High
Yemen	Labour Force Survey	2014	High
Sub-Saharan Africa			
Angola	Employment Survey	2019	High
Benin	Integrated Survey of Household Living Conditions	2018	Medium
Botswana	Multi-Topic Household Survey	2019	Medium

Burkina Faso	Regional Integrated Survey on Employment and the Informal Sector	2018	High
Burundi	Living Standards Survey	2014	Medium
Cabo Verde	Continuous Multi-Objective Survey	2015	Medium
Cameroon	Household Survey	2014	Medium
Chad	Modular and Integrated Household Survey on Living Conditions	2018	Medium
Comoros	National Survey on Employment and the Informal Sector	2014	High
CĂ´te d'Ivoire	National Survey on the Employment Situation	2019	High
DR Congo	Survey on Employment and household's living conditions	2012	High
Djibouti	Djiboutian Household Survey	2017	Medium
Eswatini	Labour Force Survey	2016	High
Ethiopia	National Labor Force Survey	2013	High
Gabon	Survey on Poverty Evaluation and Monitoring	2017	Medium
Gambia	Labour Force Survey	2018	High
Ghana	Labour Force Survey	2015	High
Guinea	National Survey on Employment and the Informal Sector	2019	High
Guinea-Bissau	Harmonized Survey on Household Living Conditions	2018	Medium
Kenya	Household Budget Survey	2019	Medium
Lesotho	Labour Force Survey	2019	High
Liberia	Labour Force Survey	2017	High
Madagascar	National Survey on Employment and the Informal Sector	2015	High
Malawi	Labour Force Survey	2013	High
Mali	Continous Household Employment Survey	2018	High
Mauritania	Living Standards Survey	2019	Medium
Mauritius	Continuous Multi-Purpose Household Survey	2019	Medium
Mozambique	Inquérito aos orçamentos familiares	2014	Low
Namibia	Labour Force Survey	2018	High
Niger	National Survey on Household Living Conditions	2014	Medium
Nigeria	Socio Economic Survey	2019	Medium
Republic of the Congo	Employment Survey	2009	High
Rwanda	Labour Force Survey	2017	High
Senegal	National Employment Survey	2019	High
Sierra Leone	Integrated Household Survey	2018	Medium
Somalia	High Frequency Survey	2017	Low
South Africa	General Household Survey	2019	High
South Sudan	High Frequency Survey	2015	Low
Tanzania	National Household Budget Survey	2012	Medium
Togo	Regional Integrated Survey on Employment and the Informal Sector	2017	High
Uganda	National Labour Force Survey	2017	High
Zambia	Labour Force Survey	2019	High
Zimbabwe	Labour Force Survey	2014	High

Table E2 – Survey Data Sources, 1990s-2000s

Country	Source	Survey Year	Quality
Europe			
Austria	EU Statistics on Income and Living Conditions	2006	High
Belarus	Household Living Standards Survey	2000	Medium
Belgium	EU Statistics on Income and Living Conditions	2006	High
Bosnia and Herzegovina	Living Standards Measurement Study	2001	Medium
Bulgaria	EU Statistics on Income and Living Conditions	2006	High
Czechia	EU Statistics on Income and Living Conditions	2006	High
Denmark	EU Statistics on Income and Living Conditions	2006	High
Estonia	EU Statistics on Income and Living Conditions	2006	High
Finland	EU Statistics on Income and Living Conditions	2006	High
France	EU Statistics on Income and Living Conditions	2006	High
Germany	EU Statistics on Income and Living Conditions	2006	High
Greece	EU Statistics on Income and Living Conditions	2006	High
Hungary	EU Statistics on Income and Living Conditions	2006	High
Iceland	EU Statistics on Income and Living Conditions	2006	High
Ireland	EU Statistics on Income and Living Conditions	2006	High
Italy	EU Statistics on Income and Living Conditions	2006	High
Latvia	EU Statistics on Income and Living Conditions	2006	High
Luxembourg	EU Statistics on Income and Living Conditions	2006	High
Malta	EU Statistics on Income and Living Conditions	2006	High
Moldova	Household Budget Survey	2001	Medium
Netherlands	EU Statistics on Income and Living Conditions	2006	High
North Macedonia	Household Budget Survey	2000	Medium
Norway	EU Statistics on Income and Living Conditions	2006	High
Poland	EU Statistics on Income and Living Conditions	2006	High
Portugal	EU Statistics on Income and Living Conditions	2006	High
Romania	EU Statistics on Income and Living Conditions	2006	High
Russia	Russia Longitudinal Monitoring Survey	2000	Medium
Serbia	Household Budget Survey	2004	Medium
Slovakia	EU Statistics on Income and Living Conditions	2006	High
Slovenia	EU Statistics on Income and Living Conditions	2006	High
Spain	EU Statistics on Income and Living Conditions	2006	High
Sweden	EU Statistics on Income and Living Conditions	2006	High
Switzerland	EU Statistics on Income and Living Conditions	2006	High
Ukraine	Household Living Conditions Survey	2002	Medium
United Kingdom	EU Statistics on Income and Living Conditions	2006	High
Northern America			
Canada	Labor Force Survey	2000	High
USA	Current Population Survey	2000	High
Latin America			
Argentina	Permanent Household Survey	2000	Medium
Barbados	Labor Force Survey	1996	High
Belize	Labor Force Survey	1999	High
Bolivia	Continuous Household Survey	2000	Medium
Brazil	National Household Sample Survey	1999	High
Chile	Chile National Socioeconomic Characterization Survey	2000	High
Colombia	Integrated Household Survey	2000	High
Costa Rica	Multipurpose Household Survey	2000	Medium
Dominican Republic	Labor Force Survey	2000	High
Ecuador	Labor Force Survey	2000	High
El Salvador	Multipurpose Household Survey	2000	Medium
Guatemala	Household Living Conditions Survey	2000	Medium
Guyana	Household Survey of Living Conditions	1999	Medium
Honduras	Multi-Purpose Permanent Household Survey	1999	Medium
Jamaica	Survey of Living Conditions	1999	Medium
Mexico	National Survey of Household Income and Expenditure	2000	Medium
Panama	Household Survey	2000	Medium
Paraguay	Permanent Household Survey	1999	High

Peru	National Household Survey	2000	Medium
Suriname	Expenditure Household Survey	1999	Medium
Trinidad and Tobago	IPUMS	2000	Medium
Uruguay	Continuous Household Survey	2000	Medium
Venezuela	Household Sampling Survey	2000	Medium
Asia			
Australia	Household, Income and Labour Dynamics Survey	2002	High
Bangladesh	Labor Force Survey	1999	High
Bhutan	Bhutan Living Standard Survey	2003	Medium
Cambodia	Labor Force Survey	2000	High
China	China Household Income Project	2002	Medium
India	Employment and Unemployment Survey	1999	High
Indonesia	National Labour Force Survey	2000	High
Iran	Household Budget Survey	2004	Medium
Kazakhstan	Household Budget Survey	2001	Medium
Lao	Lao Expenditure and Consumption Survey	2002	Medium
Maldives	Vulnerability and Poverty Assessment Survey	1998	Medium
Mongolia	Labor Force Survey	2002	High
Nepal	Labor Force Survey	1998	High
Pakistan	Labor Force Survey	1999	High
Philippines	Labor Force Survey	2001	High
South Korea	Labor Force Survey	2001	High
Thailand	Labor Force Survey	2000	High
Timor-Leste	Population and Health Survey	2001	Medium
Vietnam	Household Living Standards Survey	2002	Medium
Middle East and North Africa			
Armenia	Integrated Living Conditions Survey	1998	Medium
Cyprus	EU Statistics on Income and Living Conditions	2006	High
Egypt	Egypt Labour Market Panel Survey	1998	High
Georgia	Household Integrated Survey	2000	Medium
Jordan	Household Income and Expenditure Survey	2002	Medium
Lebanon	Living Standards Survey	2004	Medium
Morocco	Household Living Standards Survey	1998	Medium
Palestine	Labor Force Survey	2000	High
Turkey	Labor Force Survey	2002	High
Yemen	Household Budget Survey	1998	Medium
Sub-Saharan Africa			
Angola	Household Income and Expenditure Survey	2000	Medium
Botswana	Household Income and Expenditure Survey	2002	Medium
Burkina Faso	Enquête Prioritaire	1998	Medium
Burundi	Enquête Prioritaire	1998	Medium
Chad	Consumption and Informal Sector Survey	2003	Medium
CĂ´te d'Ivoire	Household Living Standards Survey	2002	Medium
Djibouti	Djibouti Household Survey	1996	Medium
Eswatini	Household Income and Expenditure Survey	2000	Medium
Gambia	High Frequency Phone Survey	1998	Medium
Ghana	Living Standards Survey	1998	Medium
Madagascar	Enquête Harmonisée sur le Conditions de Vie des Ménages	1999	Medium
Mauritania	Permanent Survey of Living Conditions of Households	2000	Medium
Mauritius	Continuous Multi-Purpose Household Survey	1999	Medium
Nigeria	Living Standards Survey	2003	Medium
Rwanda	Integrated Household Living Conditions Survey	2000	Medium
Senegal	Household Survey	2001	Medium
Sierra Leone	Integrated Household Survey	2003	Medium
South Africa	Labor Force Survey	2000	High
Uganda	National Household Survey	1999	Medium
Zambia	Living Conditions Monitoring Survey	1998	Medium

F. Data Appendix: Returns to Schooling

F.1. OLS Estimates of the Returns to Schooling

In the main analysis, I use estimates of returns to schooling by level estimated in each country. I rely on the following modified Mincerian equation:

$$\ln y_i = \alpha + \beta_{pri} D_{i,pri} + \beta_{sec} D_{i,sec} + \beta_{ter} D_{i,ter} + X_i \beta + \varepsilon_i \tag{F32}$$

With y_i earned income of individual i in a given country, $D_{i,pri}$, $D_{i,sec}$, and $D_{i,ter}$ dummies for having reached primary, secondary, and tertiary education, and X_i a vector of controls including gender, an age quartic, and interactions between gender and the age quartic. Earned income is the sum of all wage and self-employment income received by a given individual. I restrict the sample to all individuals aged 25 or above with strictly positive income. I estimate this regression separately in each country and extract estimates of β_{pri}, β_{sec}, and β_{ter}. In some surveys, there are too few observations to estimate the return to a specific education level. I choose to set returns as missing when there are less than 100 observations covering each education level—for instance, the return to primary education is set as missing if there are either less than 100 workers with no schooling or less than 100 workers with primary education. This is the case of 66 countries for the return to primary education and 24 countries for the return to secondary education. I then fill in missing values by assuming that the ratio of the missing return to that of the return to the category above is the same as in the average country. This imputation makes little difference to my results, since missing returns are those for which the share of workers with the corresponding education levels is particularly low.

One may be concerned that the estimated returns might be sensitive to alternative empirical specifications. Table F1 investigates the robustness of my results to using a standard Mincerian equation with only gender, age, and age squared as controls, as well as to restricting the dependent variable to wage income. The estimated returns are almost identical across these different specifications.

Another concern is that workers and self-employed individuals declaring positive personal income might only represent a subset of the population. This is particularly concerning in low-income countries, where a large fraction of the population often relies on subsistence agriculture and thus ends up excluded from my estimation of the returns to schooling. I investigate this concern in Appendix Table F2 by comparing three specifications. The first one corresponds to a standard Mincerian equation estimated at the individual level, restricting the sample to individuals declaring positive personal income. The second specification corresponds to a "household-level Mincerian equation," regressing per-capita expenditure on adults' average years of schooling. The third specification repeats the second specification, but after restricting the sample to households with at least one adult declaring positive personal income, which is useful to check whether the results are driven by selection into reporting positive income. I estimate these returns for eleven countries characterized by high poverty rates and large agricultural sectors: India, Pakistan, the Democratic Republic of the Congo, Burkina Faso, Côte d'Ivoire, Guinea-Bissau, Mali, Niger, Sénégal, and Togo. For each of these eleven countries, I was able to collect and manually harmonize survey microdata covering personal income, household expenditure, and educational attainment.

The three estimates fall very close to each other, with a Mincerian return typically varying from 7% to 10%. Individual returns are slightly higher than household-level returns in some countries. This is to be expected given that variations in consumption are more driven by other factors, such as savings and transfers received by other households and the government. Yet, there are also countries where individual returns are lower, such as Burkina Faso and Mali. Household-level returns before and after excluding households with no reported income are almost identical. Together, these findings provide reassuring evidence that the returns estimated in this paper provide a good approximation of the true returns to schooling for the population as a whole.

F.2. OLS Estimates of Returns Per Year of Schooling

F.2.1. Estimation Using the I2D2 Database

Figure II suggests that the returns to schooling are convex. The ILO microdata unfortunately do not allow studying heterogeneity in returns to schooling per year, because it does not cover information on completed years of schooling within each education category. For instance, the return to primary education could be low mainly because most of workers with some primary education have one or two years of schooling.

Returns Per Year of Schooling by Level To shed light on this issue, I turn to the I2D2 database. The surveys gathered in I2D2 are often the same as those used in the rest of this paper. Surveys fielded around

2019 and covering exact years of schooling are available for 62 countries. I estimate the following regression:

$$\ln y_{ic} = \alpha + \zeta^{pri} S_{ic}^{pri} + \zeta^{sec} S_{ic}^{sec} + \zeta^{ter} S_{ic}^{ter} + X_{ic}\beta + \mu_c + \varepsilon_{ic} \tag{F33}$$

Where S_{ic}^{pri}, S_{ic}^{sec}, and S_{ic}^{ter} are completed years of primary (0-6 years), secondary (7-12 years), and tertiary (above 12 years) education, respectively. X_{ic} is a vector of controls including gender, an age quartic, and interactions between gender and the age quartic. μ_c are country fixed effects. ζ^{pri}, ζ^{sec}, and ζ^{ter} can thus be interpreted as yearly returns to completing the first six years, next six years, and above twelve years of education. I run this regression separately by world region and for all countries together. I find that returns to schooling are strongly convex: the return per year of schooling is greater at higher levels of education in all world regions (see Table II).

Table F3 present results of a similar Mincerian equation but with only completed years of schooling. Table F4 also reports results of a similar regression, except that the explanatory variables are years of schooling and years of schooling squared. The coefficient on years of schooling squared is positive and statistically significant at the 1% level in all world regions.

Returns to Completed Degrees Finally, Table F5 reports results of the following regression:

$$\begin{aligned}\ln y_i = \alpha + \kappa_{pri1} D_{i,pri1} + \kappa_{pri2} D_{i,pri2} + \kappa_{sec1} D_{i,sec1} + \kappa_{sec2} D_{i,sec2} + \kappa_{ter1} D_{i,ter1} + \kappa_{ter2} D_{i,ter2} \\ + X_i\beta + \mu_c + \varepsilon_i\end{aligned} \tag{F34}$$

Where $D_{i,pri1}$, $D_{i,pri2}$, $D_{i,sec1}$, $D_{i,sec2}$, $D_{i,ter1}$, and $D_{i,ter2}$ are dummies for having reached incomplete primary, complete primary, incomplete secondary, complete secondary, incomplete tertiary, and complete tertiary education. This specification allows deriving total returns to completing a whole education cycle as:

$$\kappa_{pri} = D_{i,pri2} \tag{F35}$$

$$\kappa_{sec} = D_{i,sec2} - D_{i,pri2} \tag{F36}$$

$$\kappa_{ter} = D_{i,ter2} - D_{i,sec2} \tag{F37}$$

In other words, κ_{pri} is the return to completing primary education versus having no schooling, κ_{sec} is the return to completing secondary education versus having completed primary education, and κ_{ter} is the return to completing tertiary education versus having completed secondary education. For the definitions of complete vs. incomplete degrees, I rely on the coding of these variables that is directly reported in I2D2.

This regression is less straightforward to interpret, given that (1) primary, secondary, and tertiary cycles differ in length and (2) these lengths can vary significantly across countries. In particular, primary and secondary education typically take 6 years, while most individuals in low- and middle-income countries do not go beyond three years of tertiary education.

Table F5 reports the results of the regression. The corresponding estimates of κ_{pri}, κ_{sec}, and κ_{ter} are displayed at the bottom of the table. In all regions, the total return to primary education is lower than the total return to tertiary education, despite the latter cycle being much shorter in the majority of countries.

F.2.2. Comparison With the Previous Literature

The convexity of returns to schooling contrasts with much of the macroeconomics literature in development and growth accounting, which often assumes decreasing returns to human capital. To understand this discrepancy, it is useful to go back to previous studies documenting or assuming decreasing returns. Among seminal studies, Hall and Jones (1999) assume a return to the first four years of education of 13.4%, a return of 10.1% for the next four years, and a return of 6.8% above eight years. These figures correspond to average returns per year of schooling in Sub-Saharan Africa, the world as a whole, and OECD countries, respectively, which they take from a previous review of the literature. They do not use actual data on returns to schooling by level. Bils and Klenow (2000) adopt the same approach, concluding from the negative cross-country correlation between Mincerian returns and average years of schooling that there are diminishing returns to human capital. Unfortunately, cross-country differences in average returns may not be a good proxy for heterogeneity in returns by level within each country. In fact, returns to schooling do vary substantially across regions and are on average higher in low-income countries, despite being convex in every region.

Another influential study is Montenegro and Patrinos (2021), who exploit the I2D2 database to estimate returns to schooling in a large sample of countries from 1970 to 2014. Their analysis suggests that returns per year of schooling are highest for tertiary education and lowest for secondary education, with primary education falling in between. However, their calculation of annual returns by level contains a mistake. They estimate total returns by level using a specification similar to equation 11, but then divide each coefficient by the number of years of schooling in each category instead of taking the exponent. For instance, they estimate the return to a year of primary education as $\gamma_c^{pri} = \beta_c^{pri}/L^{pri}$, with L^{pri} the number of years of primary education, while the true formula should be $\gamma_c^{pri} = \exp\left(\beta_c^{pri}\right)^{1/L^{pri}} - 1$. This might explain why they find higher returns to primary education than to secondary education, in contrast with my analysis using the same database. Another reason might be that they restrict the analysis to wage earners, while my estimates cover both wage earners and the self-employed.

My results are more consistent with recent estimates of the returns to schooling. For instance, Jedwab et al. (2023) document much higher returns per year of schooling for workers with more than 13 years of schooling in the I2D2 database. Similarly, Rossi (2022) finds clear evidence of convex returns to schooling in a sample of twelve developed and developing countries.

Table F1 – Returns to Schooling: Sensitivity to Alternative Specifications

	(1)	(2)	(3)	(4)
Primary	0.157***	0.153***	0.135***	0.135***
	(0.007)	(0.007)	(0.010)	(0.010)
Secondary	0.524***	0.511***	0.543***	0.532***
	(0.006)	(0.006)	(0.007)	(0.007)
Tertiary	1.079***	1.054***	1.069***	1.047***
	(0.007)	(0.007)	(0.008)	(0.008)
Extended Model	No	Yes	No	Yes
Depvar = Log Wage	No	No	Yes	Yes
N	5,103,826	5,103,826	3,839,134	3,839,134
Adj. R-squared	0.82	0.82	0.88	0.88

Notes. The table reports estimates of total returns to schooling, comparing models with "standard" versus "extended" controls, as well as models using the log of personal income versus the log of wages as the dependent variable. Standard model: controls for gender, age, and age squared. Extended model: controls for gender, an age quartic, and interactions between gender and the age quartic, as in Lemieux (2006). Depvar = log wage: the dependent variable is the log of wages rather than the log of total personal income. Pooled regression across all countries. All estimates include country fixed effects. Observations are weighted to match each country's total population. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table F2 – Returns to Schooling: Personal Income Versus Per-Capita Consumption

	Individual Income	Consumption All Households	Consumption Households With Income Only
India	0.070***	0.063***	0.063***
	(0.001)	(0.001)	(0.001)
Pakistan	0.074***	0.071***	0.071***
	(0.001)	(0.001)	(0.001)
DR Congo	0.075***	0.071***	0.070***
	(0.002)	(0.002)	(0.002)
Burkina Faso	0.089***	0.106***	0.086***
	(0.006)	(0.003)	(0.005)
Benin	0.078***	0.068***	0.071***
	(0.003)	(0.002)	(0.003)
Côte d'Ivoire	0.073***	0.058***	0.052***
	(0.003)	(0.002)	(0.002)
Guinea-Bissau	0.041***	0.061***	0.052***
	(0.004)	(0.002)	(0.003)
Mali	0.072***	0.080***	0.061***
	(0.005)	(0.002)	(0.003)
Niger	0.108***	0.103***	0.101***
	(0.004)	(0.003)	(0.003)
Sénégal	0.078***	0.074***	0.075***
	(0.003)	(0.002)	(0.002)
Togo	0.100***	0.078***	0.076***
	(0.006)	(0.002)	(0.005)

Notes. The table compares returns to schooling estimated with three specifications. The first specification regresses individual income on individual years of schooling, controlling for age, gender, and their interaction. The second specification regresses per-capita consumption on average years of schooling of working-age adults at the household level, controlling for household size, average age, and the share of women. The third specification does the same, but after restricting the sample to households with at least one adult declaring positive personal income. India: 2019 PLFS survey. Pakistan: 2018 HIES survey. DR Congo: 2012 ECM survey. Other countries: 2018 EHCVM surveys. Robust standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table F3 – Returns Per Year of Schooling: Pooled Regression Results

	(1) All Countries	(2) Latin America	(3) China	(4) India	(5) Other Asia	(6) MENA	(7) Sub-Saharan Africa
Years of Schooling	0.076***	0.096***	0.092***	0.063***	0.057***	0.020***	0.097***
	(0.000)	(0.000)	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)
N	1,285,895	781,577	30,036	122,870	119,548	78,881	152,983
R Squared	0.78	0.88	0.21	0.35	0.91	0.74	0.79

Notes. The table reports results of pooled regressions relating the log of personal income to years of schooling. The full sample covers 62 countries with information on exact completed years of schooling. All estimates include country fixed effects and control for gender, an age quartic, and interactions between gender and the age quartic. Observations are weighted to match the total population of each country.

Table F4 – Returns Per Year of Schooling: Pooled Regression Results with Years of Schooling Squared

	(1) All Countries	(2) Latin America	(3) China	(4) India	(5) Other Asia	(6) MENA	(7) Sub-Saharan Africa
Years of Schooling	0.002*	0.075***	0.052***	-0.020***	0.011***	-0.001	0.005
	(0.001)	(0.001)	(0.008)	(0.002)	(0.001)	(0.001)	(0.004)
Years of Schooling Squared	0.004***	0.001***	0.002***	0.005***	0.003***	0.001***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	1,285,895	781,577	30,036	122,870	119,548	78,881	152,983
R Squared	0.79	0.88	0.21	0.38	0.91	0.74	0.79

Notes. The table reports results of pooled regressions relating the log of personal income to years of schooling and years of schooling squared. The full sample covers 62 countries with information on exact completed years of schooling. All estimates include country fixed effects and control for gender, an age quartic, and interactions between gender and the age quartic. Observations are weighted to match the total population of each country.

Table F5 – Returns to Detailed Educational Attainment Categories: Pooled Regression Results

	(1) All Countries	(2) Latin America	(3) China	(4) India	(5) Other Asia	(6) MENA	(7) Sub-Saharan Africa
Incomplete Primary	0.063***	0.312***	0.198*	0.098***	0.011	0.039	0.056***
	(0.014)	(0.018)	(0.105)	(0.011)	(0.016)	(0.034)	(0.022)
Complete Primary	0.196***	0.505***	0.389***	0.144***	0.238***	0.137***	0.132***
	(0.014)	(0.018)	(0.105)	(0.014)	(0.021)	(0.041)	(0.022)
Incomplete Secondary	0.391***	0.713***	0.579***	0.233***	0.247***	0.213***	0.393***
	(0.014)	(0.018)	(0.103)	(0.010)	(0.014)	(0.036)	(0.021)
Complete Secondary	0.630***	0.921***	0.853***	0.406***	0.499***	0.229***	0.627***
	(0.014)	(0.017)	(0.104)	(0.012)	(0.015)	(0.025)	(0.024)
Incomplete Tertiary	0.903***	1.205***	1.042***	0.809***	0.658***	0.289***	0.989***
	(0.015)	(0.018)	(0.105)	(0.023)	(0.019)	(0.038)	(0.025)
Complete Tertiary	1.185***	1.648***	1.258***	1.087***	0.811***	0.529***	1.271***
	(0.014)	(0.017)	(0.104)	(0.014)	(0.016)	(0.025)	(0.022)
Compl. Primary vs. No Schooling	0.20	0.50	0.39	0.14	0.24	0.14	0.13
Compl. Secondary vs. Compl. Primary	0.43	0.42	0.46	0.26	0.26	0.09	0.49
Compl. Tertiary vs. Compl. Secondary	0.56	0.73	0.40	0.68	0.31	0.30	0.64
N	1,291,371	781,614	30,036	122,870	119,659	78,910	158,282
R Squared	0.89	0.92	0.21	0.37	0.94	0.91	0.82

Notes. The table reports results of pooled regressions relating the log of personal income to dummies taking 1 if the individual has the corresponding level of educational attainment and 0 otherwise. Each coefficient thus captures the return to reaching a specific educational attainment category with respect to having no schooling. Returns to completing full cycles of education are reported at the bottom of the table. The full sample covers 62 countries with detailed educational attainment information. All estimates include country fixed effects and control for gender, an age quartic, and interactions between gender and the age quartic. Observations are weighted to match the total population of each country.

G. Data Appendix: Educational Attainment and Income Distribution Data

G.1. Educational Attainment Data

Barro-Lee Database The primary data source used to measure the evolution of educational attainment is the database compiled by Barro and Lee (2013) and updates.[6] The database covers the distribution of educational attainment by age group and gender in 146 countries at five year intervals from 1950 to 2015. It covers 123 countries out of the 150 countries studied in this paper. The education categories are no schooling, incomplete primary, complete primary, incomplete secondary, complete secondary, incomplete tertiary, and complete tertiary. I interpolate linearly the share of individuals belonging to each category between missing years, and extrapolate linearly educational attainment by age and gender after 2015, so as to cover the entire 1980-2019 period.

IPUMS and Survey Data For the 27 countries absent from the Barro-Lee database, I rely on census and survey data. For Burkina Faso (1985-2006), Ethiopia (1984-2007), Guinea (1983-2014), and Palestine (1997-2017), the data source is the census microdata samples available from IPUMS International. For India, which is covered by the Barro-Lee database but displays somewhat erratic trends, I rely instead on the education modules of the national sample survey (1983-2017), which I collected and harmonized for the purpose of this paper. For the remaining 22 countries, in the absence of better data, I use cohort-level trends in educational attainment observed in the surveys collected in this paper.[7] I first aggregate the distribution of educational attainment by cohort and gender in each survey. I linearly interpolate and extrapolate when needed, so as to cover all cohorts born since 1915-1920 (aged 60-65 in 1980). I then derive estimates of educational attainment of the 1980 to 2019 working-age populations by taking the weighted average across cohorts belonging to the working-age population in the corresponding year.

Matching Survey and Aggregate Data To derive accurate estimates of counterfactual income absent educational expansion, it is important to make sure that educational attainment in the survey data matches perfectly aggregate data used to derive the counterfactual. Although education levels do correlate strongly in the two sources, some inconsistencies remain. For instance, aggregate and survey data sometimes report

[6] See http://www.barrolee.com/.

[7] The countries are Angola, Azerbaijan, Bosnia and Herzegovina, Bhutan, Belarus, Cabo Verde, Cambodia, Chad, Djibouti, Georgia, Guinea-Bissau, Kosovo, Lebanon, Montenegro, Madagascar, Macedonia, Nigeria, Somalia, Suriname, South Sudan, Timor-Leste, and Uzbekistan.

incomplete degrees as complete and sometimes do not, or code lower secondary education as primary education. To make sure that the two sources coincide, I first manually recode some categories in survey and/or aggregate data, country by country, by visually inspecting the distribution of educational attainment in the two sources. The result of this manual recoding process is displayed in figures G1a, G1b, G1c, and G1d, which compare the share of the working-age population with no schooling, primary/basic education, secondary education, and tertiary education in survey versus aggregate data. The two sources end up very close to each other after recoding.

Second, I perform a final small adjustment to the sample weights of each survey to make sure that education levels by age and gender match perfectly in the two sources. I combine aggregate data on the distribution of attainment with data on total population by age and gender from the UN to derive estimates of the total number of individuals belonging to each of 40 education-age-gender cells. I then use linear calibration to ensure that total weights match the total population belonging to each cell in each country. The result is a new weight variable that ensures that the distribution of educational attainment by age and gender (and for the working-age population as a whole) in the survey data matches perfectly that observed in aggregate data.

G.2. Income Distribution Data

The final step of the distributional growth accounting exercise consists in moving from labor income to total income, and comparing counterfactual to actual real income growth rates. This requires data on the distribution of income in each country, aggregate labor and capital income shares, and the share of income received from labor and capital by income group within each country.

Pretax Income Inequality Data Data on the world distribution of income come from the World Inequality Database (WID). It reports average per-capita pretax income by percentile in all countries in the world from 1980 to 2019. The income concept is pretax national income, that is, total income received by individuals before accounting for taxes and transfers, but after accounting for the operation of pension and unemployment systems. Importantly, all components of net national income (GDP, minus consumption of fixed capital, plus net foreign income) are allocated to individuals, following the Distributional National Accounts (DINA) framework (see Chancel et al., 2022; Piketty, Saez, and Zucman, 2018). This ensures that all income distributions are consistent with macroeconomic growth rates and aggregate capital and labor income shares recorded in the national accounts. The database is constructed by compiling estimates from detailed national or regional studies, which combine surveys, tax data, and national accounts to construct distributions that are conceptually comparable across countries (see for instance Piketty, Saez, and Zucman (2018) on the United States, Blanchet, Chancel, and Gethin (2022) on Europe, and De Rosa, Flores, and Morgan (2022) on Latin America).

Aggregate Labor and Capital Income Shares Aggregate factor income shares come from Bachas et al. (2022), who combine a number of sources to build a new database on the components of net national income worldwide since 1965. Their database provides a decomposition of net domestic product into compensation of employees, mixed income, the operating surplus of households (actual and imputed rental income), and the operating surplus of corporations (profits net of depreciation).

I define the labor income share as the share of income attributable to compensation of employees and mixed income. This is the definition of the labor share that is the most conceptually meaningful in my context, given that my microdata cover individual income and returns to schooling for both wage earners and the self-employed. In the main analysis, I thus make the conservative assumption that human capital only affects wages and mixed income, while leaving capital income unchanged.

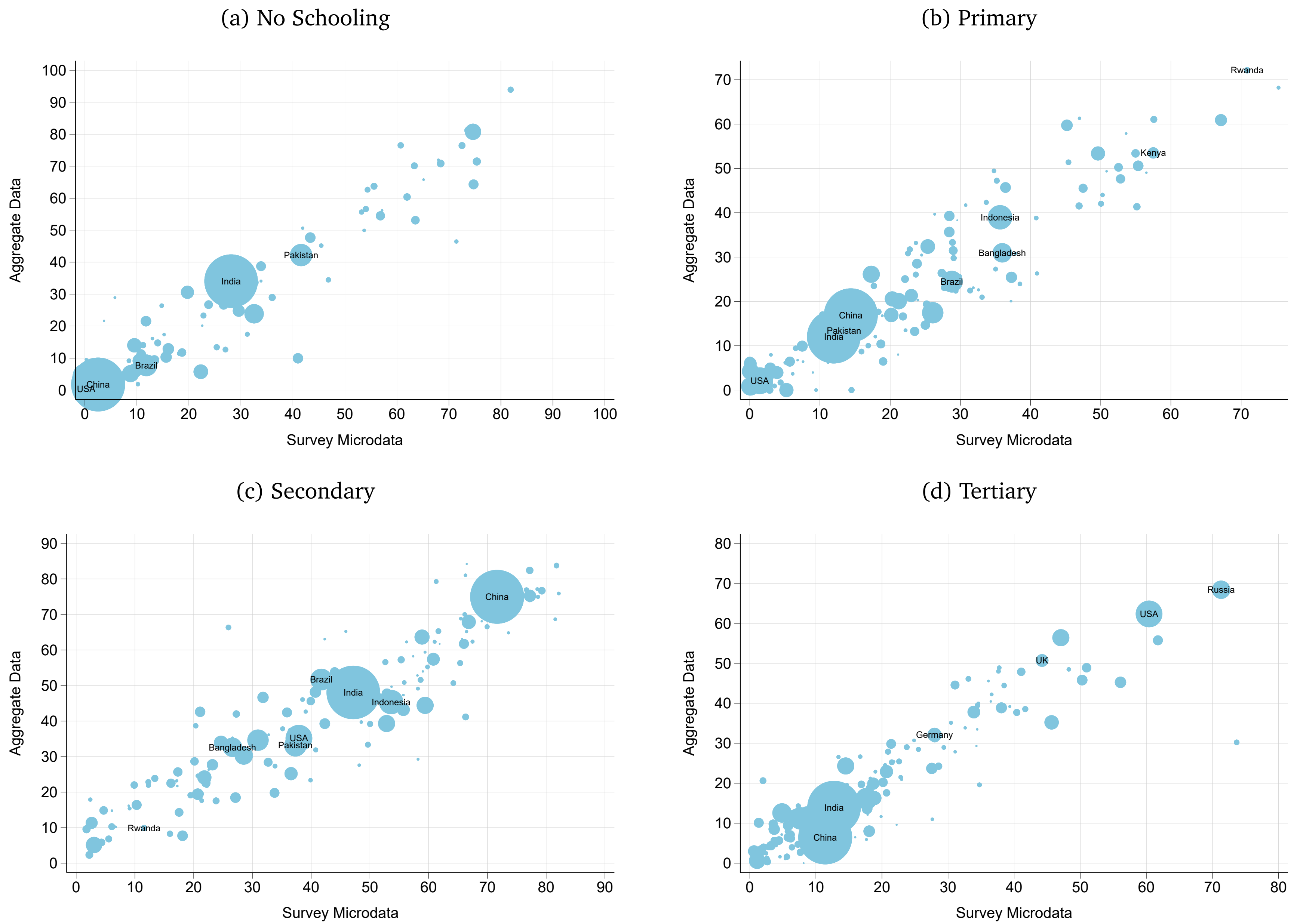
Capital Income Concentration The last step is to estimate how the capital income share varies alongside the income distribution in each country. Data on this decomposition are scarce. Drawing on selected high-quality studies, I was able to derive such profiles for the United States (Piketty, Saez, and Zucman, 2018), South Africa (Chatterjee, Czajka, and Gethin, 2022), and 10 Latin American countries (De Rosa, Flores, and Morgan, 2022). The corresponding series are plotted in Appendix Figure G2. The profiles look very similar across these three cases. The capital share is always below 20% for the bottom 90% of earners, corresponding mostly to imputed rental income. It rises exponentially at the very top of the distribution, where the main source of income is from bonds and stock. Given these similarities, I use the average profile observed across countries, which I rescale in each country-year to match the aggregate capital income share.

World Bank Income Distribution Data I also report results using World Bank consumption and income distribution data instead of the World Inequality Database. The database is available from the World Bank's Poverty and Inequality Platform (PIP), and presents itself in the form of distributions available for selected countries and years. The income concept is either consumption or posttax disposable income per capita, depending on the country. All values are reported in 2017 PPP USD per day.

Unfortunately, although the World Bank regularly reports indicators of global poverty, it does not publish underlying estimates of the world distribution of income. I thus attempt to reconstruct measures of pretax and posttax income myself. Starting from available data, I first extrapolate the average income of each country-percentile to missing years using real GDP per capita growth rates. For the 17 countries entirely missing, I use estimates from the World Inequality Database. The resulting database yields trends in global poverty almost identical to those officially reported by the World Bank. I then reconstruct measures of pretax income. In the absence of any information on savings, I define pretax income in each country as consumption or disposable income, minus social assistance transfers, plus direct taxes. The distribution of social assistance transfers and direct taxes come from two companion papers (Fisher-Post and Gethin, 2023; Gethin, 2024).

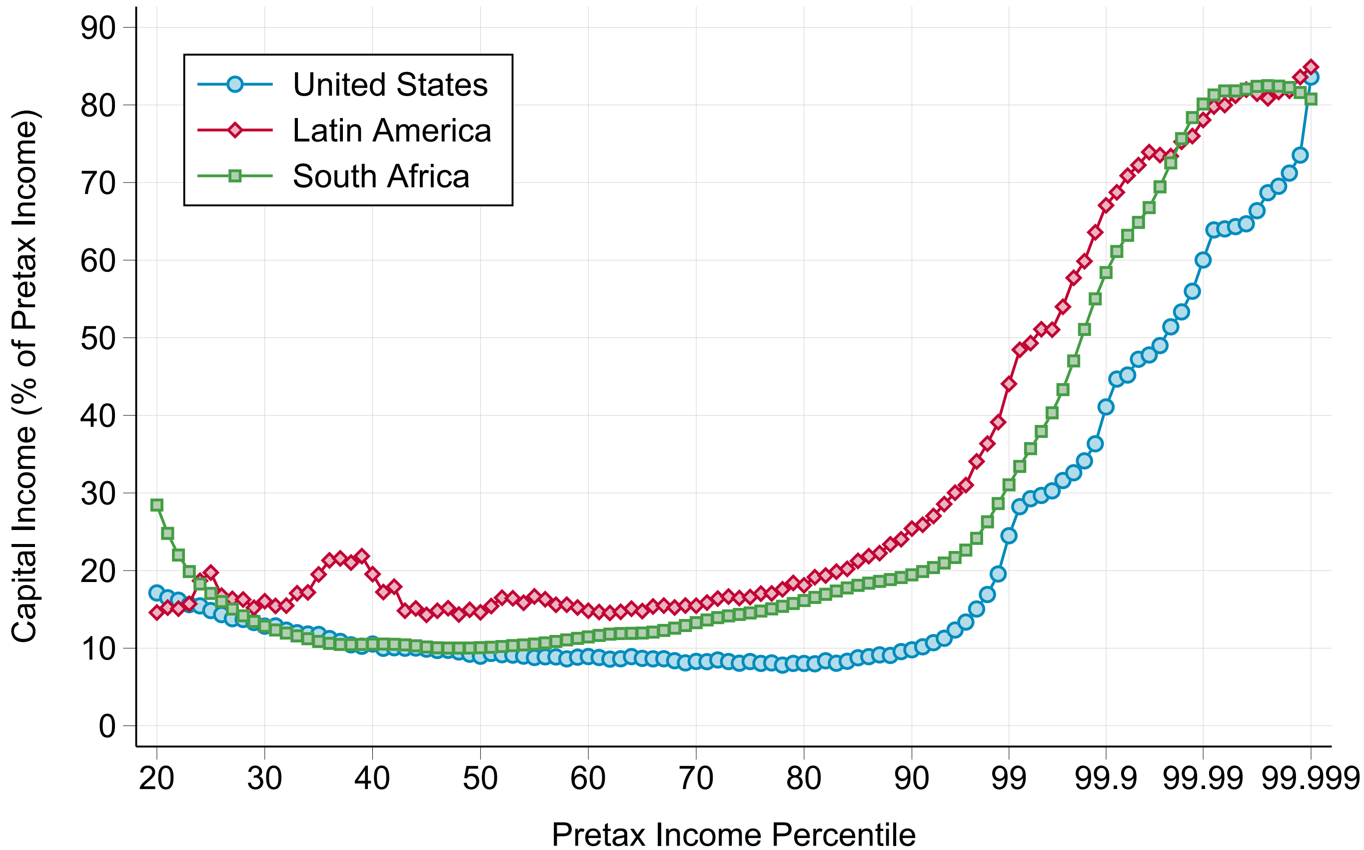
Both the levels and trends in global poverty in the WID data differ from those of the World Bank for at least four main reasons. First, World Bank estimates mostly focus on consumption (posttax disposable income minus net household saving), while my focus here is on income. The difference between consumption and income can be large, with major implications for levels and trends in inequality in some cases (see for instance Chancel et al., 2023). Second, the estimates presented here are consistent with national income growth rates, while World Bank estimates are based on surveys and do not attempt to bridge gaps between survey and national accounts aggregates. Third, some of the estimates used in this paper are based on detailed country-specific studies that rely on data sources that may differ from those of the World Bank in a number of countries, including China (Piketty, Yang, and Zucman, 2019), India (Chancel and Piketty, 2019), and Latin America (De Rosa, Flores, and Morgan, 2022). See Chancel and Piketty (2021). Fourth, I use GDP purchasing power parity conversion factors, while the World Bank only corrects for price differences in household final consumption expenditure. For all these reasons, I view the World Inequality Database as a more adequate source for conducting the particular analysis developed in this paper. A more systematic comparison of these two datasets is left to future research.

Figure G1 – Distribution of Educational Attainment in Barro-Lee Versus Survey Data (% of Working-Age Population)



Notes. The figure compares estimates of the share of the working-age population with no schooling, primary, secondary, and tertiary education in the survey microdata (x-axis) and aggregate data from Barro and Lee (2013) and other sources (y-axis), after manual reclassification of educational categories in each country.

Figure G2 – The Concentration of Capital Income
in the United States, Latin America, and South Africa



Notes. The figure plots the capital income share by pretax income percentile in the United States, South Africa, and Latin America in 2019. Capital income is defined as all income other than compensation of employees and mixed income. Author's elaboration combining data from Piketty, Saez, and Zucman (2018) for the United States, De Rosa, Flores, and Morgan (2022) for Latin America, and Chatterjee, Czajka, and Gethin (2021) for South Africa.

References

Aakvik, Arild, Kjell G. Salvanes, and Kjell Vaage (2010). "Measuring Heterogeneity in the Return to Education Using and Education Reform". In: *European Economic Review* 54.1, pp. 483–500.

Acemoglu, Daron and Joshua Angrist (2000). "How Large Are Human-Capital Externalities? Evidence from Compulsory Schooling Laws". In: *NBER Macroeconomics Annual* 15.1, pp. 9–59.

Acemoglu, Daron and David Autor (2011). "Skills, Tasks and Technologies: Implications for Employment and Earnings". In: *Handbook of Labor Economics, Volume 4B*. Ed. by Orley Ashenfelter and David Card. North Holland, pp. 1043–1171.

Akresh, Richard, Daniel Halim, and Marieke Kleemans (2023). "Long-Term and Intergenerational Effects of Education: Evidence from School Construction in Indonesia". In: *The Economic Journal* 133.650, pp. 582–612.

Altinok, Nadir, Noam Angrist, and Harry A. Patrinos (2018). "Global Data Set on Education Quality (1965-2015)". World Bank Policy Research Working Paper No. 8314.

Alzúa, María Laura, Leonardo Gasparini, and Francisco Haimovich (2015). "Education Reform and Labor Market Outcomes: The Case of Argentina's Ley Federal de Educación". In: *Journal of Applied Economics* 18.1, pp. 21–44.

Angrist, Joshua D. (1995). "The Economic Returns to Schooling in the West Bank and Gaza Strip". In: *The American Economic Review* 85.5, pp. 1065–1087.

Angrist, Noam, Simeon Djankov, Pinelopi K. Goldberg, and Harry A. Patrinos (2021). "Measuring human capital using global learning data". In: *Nature* 592.1, pp. 403–408.

Assaad, Ragui, Abdurrahman B. Aydemir, Meltem Dayıoglu, and Murat Güray Kırdar (2023). "Wage Returns to Human Capital Resulting from an Extra Year of Primary School: Evidence from Egypt". IZA Discussion Paper.

Autor, David, Claudia Goldin, and Lawrence F. Katz (2020). "Extending the Race between Education and Technology". In: *AEA Papers and Proceedings* 110.1, pp. 347–351.

Aydemir, Abdurrahman and Murat G. Kirdar (2017). "Low Wage Returns to Schooling in a Developing Country: Evidence from a Major Policy Reform in Turkey". In: *Oxford Bulletin of Economics and Statistics* 79.6, pp. 1046–1086.

Bachas, Pierre, Matthew H. Fisher-Post, Anders Jensen, and Gabriel Zucman (2022). "Globalization and Factor Income Taxation". NBER Working Paper 29819.

Barro, Robert J. and Jong-Wha Lee (2013). "A new data set of educational attainment in the world, 1950–2010". In: *Journal of Development Economics* 104.1, pp. 184–198.

Bhuller, Manudeep, Magne Mogstad, and Kjell G. Salvanes (2017). "Life-Cycle Earnings, Education Premiums, and Internal Rates of Return". In: *Journal of Labor Economics* 35.4, pp. 993–1030.

Bils, Mark, Baris Kaymak, and Kai-Jie Wu (2022). "Labor Substitutability Among Schooling Groups". NBER Working Paper.

Bils, Mark and Peter J. Klenow (2000). "Does Schooling Cause Growth". In: *American Economic Review* 90.5, pp. 1160–1183.

Blanchet, Thomas, Lucas Chancel, and Amory Gethin (2022). "Why Is Europe More Equal Than the United States?" In: *American Economic Journal: Applied Economics* 14.4, pp. 1–40.

Bowlus, Audra, Lance Lochner, Chris Robinson, and Eda Suleymanoglu (2021). "Wages, Skills, and Skill-Biased Technical Change: The Canonical Model Revisited". Working Paper.

Brunello, Giorgio, Margherita Fort, and Guglielmo Weber (2009). "Changes in Compulsory Schooling, Education and the Distribution of Wages in Europe". In: *The Economic Journal* 119.536, pp. 516–539.

Brunello, Giorgio, Guglielmo Weber, and Christoph T. Weiss (2015). "Books are Forever: Early Life Conditions, Education and Lifetime Earnings in Europe". In: *The Economic Journal* 127.600, pp. 271–296.

Buscha, Franz and Matt Dickson (2012). "The Raising of the School Leaving Age: Returns in Later Life". In: *Economics Letters* 117.1, pp. 389–393.

— (2015). "The Wage Returns to Education over the Life-Cycle: Heterogeneity and the Role of Experience". IZA Discussion Paper.

Calonico, Sebastian, Matias D. Cattaneo, and Rocío Titiunik (2014). "Robust Nonparametric Confidence Intervals for Regression-Discontinuity Designs". In: *Econometrica* 82.6, 2295–2326.

Card, David and Thomas Lemieux (2001). "Can Falling Supply Explain the Rising Return to College for Younger Men? A Cohort-Based Analysis". In: *The Quarterly Journal of Economics* 116.2, pp. 705–746.

Carneiro, Pedro, Michael Lokshin, and Nithin Umapathi (2017). "Average and Marginal Returns to Upper Secondary Schooling in Indonesia". In: *Journal of Applied Econometrics* 32.1, pp. 16–36.

Caselli, Francesco (2016). *Technology Differences over Space and Time*. CREI Lectures in Macroeconomics.

Caselli, Francesco and Wilbur John II Coleman (2006). "The World Technology Frontier". In: *American Economic Review* 96.3, pp. 499–522.

Chancel, Lucas, Denis Cogneau, Alix Myczkowski, and Anne-Sophie Robilliard (2023). "Income Inequality in Africa, 1990-2019: Measurement, Patterns, Determinants". In: *World Development* 163.1, pp. 106–162.

Chancel, Lucas and Thomas Piketty (2019). "Indian Income Inequality, 1922-2015: From British Raj to Billionaire Raj?" In: *Review of Income and Wealth* 65.S1, S33–S62.

— (2021). "Global Income Inequality, 1820–2020: the Persistence and Mutation of Extreme Inequality". In: *Journal of the European Economic Association* 19.6, 3025–3062.

Chancel, Lucas, Thomas Piketty, Emmanuel Saez, and Gabriel Zucman (2022). *World Inequality Report 2022*. Harvard University Press.

Chatterjee, Aroop, Léo Czajka, and Amory Gethin (2021). "Can Redistribution Keep Up with Inequality? Evidence from South Africa, 1993-2019". Working Paper.

— (2022). "Wealth Inequality in South Africa, 1993-2017". In: *World Bank Economic Review* 36.1, pp. 19–36.

Ciccone, Antonio and Giovanni Peri (2005). "Long-Run Substitutability Between More and Less Educated Workers: Evidence from U.S. States, 1950-1990". In: *The Review of Economics and Statistics* 87.4, pp. 652–663.

— (2006). "Identifying Human-Capital Externalities: Theory with Applications". In: *Review of Economic Studies* 73.1, pp. 381–412.

Clark, Damon (2023). "School quality and the return to schooling in Britain: New evidence from a large-scale compulsory schooling reform". In: *Journal of Public Economics* 223.1, pp. 1049–1102.

Clay, Karen, Jeff Lingwall, and Melvin Jr. Stephens (2021). “Laws, educational outcomes, and returns to schooling evidence from the first wave of U.S. state compulsory attendance laws”. In: *Labour Economics* 68.1, pp. 1019–1035.

De Rosa, Mauricio, Ignacio Flores, and Marc Morgan (2022). “More Unequal or Not as Rich? Revisiting the Latin American Exception”. Stone Center for Inequality Studies Working Paper Series.

Delaney, Judith M. and Paul J. Devereux (2019). “More Education, Less Volatility? The Effect of Education on Earnings Volatility over the Life Cycle”. In: *Journal of Labor Economics* 37.1, pp. 101–137.

Delesalle, Esther (2021). “The effect of the Universal Primary Education program on consumption and on the employment sector: Evidence from Tanzania”. In: *World Development* 142.1, pp. 1053–1070.

Denny, Kevin J. and Colm P. Harmon (2000). “Education Policy Reform and the Return to Schooling from Instrumental Variables”. Working Paper.

Devereux, Paul J. and Robert A. Hart (2010). “Forced to be Rich? Returns to Compulsory Schooling in Britain”. In: *The Economic Journal* 120.549, pp. 1345–1364.

Dickson, Matt (2013). “The Causal Effect of Education on Wages Revisited”. In: *Oxford Bulletin of Economics and Statistics* 75.4, pp. 477–498.

Dolton, Peter and Matteo Sandi (2017). “Returning to returns: Revisiting the British education evidence”. In: *Labour Economics* 48.1, pp. 87–104.

Domnisoru, Ciprian (2021). “Heterogeneity across Families in the Impact of Compulsory Schooling Laws”. In: *Economica* 88.1, pp. 399–429.

Duflo, Esther (2001). “Schooling and Labor Market Consequences of School Construction in Indonesia: Evidence from an Unusual Policy Experiment”. In: *American Economic Review* 91.4, pp. 795–813.

— (2004). “The medium run effects of educational expansion: evidence from a large school construction program in Indonesia”. In: *Journal of Development Economics* 74.1, pp. 163–197.

Duflo, Esther, Pascaline Dupas, and Michael Kremer (2024). “The Impact of Secondary School Subsidies on Career Trajectories in a Dual Labor Market: Experimental Evidence from Ghana”. Working Paper.

Eble, Alex and Feng Hu (2019). “Does primary school duration matter? Evaluating the consequences of a large Chinese policy experiment”. In: *Economics of Education Review* 70.1, pp. 61–74.

Fabregas, Raissa and Laia Navarro-Sola (2024). “Broadcasting Education at Scale: Long-Term Labor Market Impacts of Television-Based Schools”. Working paper.

Fan, Elliott, Xin Meng, Zhichao Wei, and Guochang Zhao (2018). “Rates of Return to Four-Year University Education: An Application of Regression Discontinuity Design”. In: *Scandinavian Journal of Economics* 120.4, 1011–1042.

Fang, Hai, Karen N. Eggleston, John A. Rizzo, Scott Rozelle, and Richard J. Zeckhauser (2012). “The Returns to Education in China: Evidence from the 1986 Compulsory Education Law”. NBER Working Paper.

Fernández, Manuel and Julián Messina (2018). “Skill premium, labor supply, and changes in the structure of wages in Latin America”. In: *Journal of Development Economics* 135.1, pp. 555–573.

Filmer, Deon and Norbert Schady (2014). “The Medium-Term Effects of Scholarships in a Low-Income Country”. In: *Journal of Human Resources* 49 (3), pp. 663–694.

Fischer, Martin, Martin Karlsson, Therese Nilsson, and Nina Schwarz (2019). “The Long-Term Effects of Long Terms - Compulsory Schooling Reforms in Sweden”. In: *Journal of the European Economic Association* 18.6, 2776–2823.

Fisher-Post, Matthew and Amory Gethin (2023). “Government Redistribution and Development: Global Estimates of Tax-and-Transfer Progressivity, 1980-2019”. Working Paper.

Gethin, Amory (2024). “Revisiting Global Poverty Reduction: Public Goods and the World Distribution of Income, 1980-2022”. Working Paper.

Goldin, Claudia and Lawrence F. Katz (2007). “The Race between Education and Technology: The Evolution of U.S. Educational Wage Differentials, 1890 to 2005”. NBER Working Paper.

Grenet, Julien (2013). “Is Extending Compulsory Schooling Alone Enough to Raise Earnings? Evidence from French and British Compulsory Schooling Laws”. In: *The Scandinavian Journal of Economics* 115.1, 176–210.

Guo, Junjie, Nicolas Roys, and Ananth Seshadri (2018). “Estimating Aggregate Human Capital Externalities”. Working Paper.

Hall, Robert E. and Charles I. Jones (1999). “Why Do Some Countries Produce So Much More Output Per Worker Than Others?” In: *The Quarterly Journal of Economics* 114.1, pp. 83–116.

Hanushek, Eric A., Jens Ruhose, and Ludger Woessman (2017). “Knowledge Capital and Aggregate Income Differences: Development Accounting for US States”. In: *American Economic Journal: Macroeconomics* 9.4, pp. 184–224.

Harmon, Colm and Ian Walker (1995). “Estimates of the Economic Return to Schooling for the United Kingdom”. In: *The American Economic Review* 85.5, pp. 1278–1286.

Heckman, James J., Lance Lochner, and Christopher Taber (1998). “Explaining Rising Wage Inequality: Explorations with a Dynamic General Equilibrium Model of Labor Earnings with Heterogeneous Agents”. In: *Review of Economic Dynamics* 1.1, pp. 1–58.

Hendricks, Lutz and Todd Schoellman (2023). “Skilled Labor Productivity and Cross-Country Income Differences”. In: *American Economic Journal: Macroeconomics* 15.1, pp. 240–268.

Hermo, Santiago, Miika Päällysaho, David Seim, and Jesse Shapiro (2022). “Labor Market Returns and the Evolution of Cognitive Skills: Theory and Evidence”. In: *Quarterly Journal of Economics* 137.4, pp. 2309–2361.

Hershbein, Brad, Melissa S. Kearney, and Luke W. Pardue (2020). “College Attainment, Income Inequality, and Economic Security: A Simulation Exercise”. In: *AEA Papers and Proceedings* 110.1, pp. 352–355.

Hicks, Daniel and Huiqiong Duan (2023). “Education as opportunity? The causal effect of education on labor market outcomes in Jordan”. In: *Oxford Development Studies* 51.2, pp. 179–197.

Hsiao, Allan (2023). “Educational Investment in Spatial Equilibrium: Evidence from Indonesia”. Working Paper.

Huang, Bin and Yu Zhu (2022). “Returns to education in China: Evidence from the great higher education expansion”. In: *China Economic Review* 74, pp. 1018–1104.

Imbens, Guido W. and Karthik Kalyanaraman (2012). “Optimal Bandwidth Choice for the Regression Discontinuity Estimator”. In: *Review of Economic Studies* 79.3, pp. 933–959.

Iranzo, Susana and Giovanni Peri (2009). "Schooling Externalities, Technology, and Productivity: Theory and Evidence from U.S. States". In: *The Review of Economics and Statistics* 91.2, pp. 420–431.

Jedwab, Remi, Paul Romer, Asif M. Islam, and Roberto Samaniego (2023). "Human Capital Accumulation at Work: Estimates for the World and Implications for Development". In: *American Economic Journal: Macroeconomics* 15.3, pp. 191–223.

Karachiwalla, Naureen and Giordano Palloni (2019). "Human Capital and Structural Transformation: Quasi-Experimental Evidence from Indonesia". Working Paper.

Katz, Lawrence F. and Kevin M. Murphy (1992). "Changes in Relative Wages, 1963-1987: Supply and Demand Factors". In: *The Quarterly Journal of Economics* 107.1, pp. 35–78.

Khanna, Gaurav (2023). "Large-Scale Education Reform in General Equilibrium: Regression Discontinuity Evidence from India". In: *Journal of Political Economy* 131.2, pp. 549–591.

Korwatanasakul, Upalat (2023). "Returns to Schooling in Thailand: Evidence from the 1978 Compulsory Schooling Law". In: *The Developing Economies* 61.1, pp. 3–35.

Kuwait, Estimating Long-Term Impacts of Wartime Schooling Disruptions on Private Returns to Schooling in (2024). "The Long Shadow of Short-Term Schooling Disruption". In: *Journal of Labor Research* 45.1, 111–152.

Kyui, Natalia (2016). "Expansion of higher education, employment and wages: Evidence from the Russian Transition". In: *Labour Economics* 39.1, pp. 68–87.

Le Nestour, Alexis, Laura Moscoviz, and Justin Sandefur (2022). "The Long-Run Decline of Education Quality in the Developing World". Working Paper.

Leigh, Andrew and Chris Ryan (2008). "Estimating returns to education using different natural experiment techniques". In: *Economics of Education Review* 27.1, 149–160.

Lemieux, Thomas (2006). "The "Mincer Equation" Thirty Years After Schooling, Experience, and Earnings". In: *Jacob Mincer. A Pioneer of Modern Labor Economics*. Ed. by Shoshana Grossbard. Springer. Chap. 11, 127–145.

Lemieux, Thomas and David Card (2001). "Education, Earnings, and the 'Canadian G.I. Bill'". In: *The Canadian Journal of Economics / Revue canadienne d'Economique* 34.2, pp. 313–344.

Li, Sophie (2024). "Returns to Education for Women in the Mid-Twentieth Century: Evidence from Compulsory Schooling Laws". Working Paper.

Liwiński, Jacek (2020). "The Impact of Compulsory Schooling on Hourly Wage: Evidence From the 1999 Education Reform in Poland". In: *Evaluation Review* 44.5, pp. 437–470.

Meghir, Costas and Marten Palme (1999). "Assessing the Effect of Schooling on Earnings Using a Social Experiment". Working Paper.

— (2005). "Educational Reform, Ability, and Family Background". In: *American Economic Review* 95.1, pp. 414–424.

Montenegro, Claudio E. and Harry Anthony Patrinos (2021). "A data set of comparable estimates of the private rate of return to schooling in the world, 1970–2014". In: *International Journal of Manpower* 1.1, pp. 1–20.

Murphy, Kevin M., W. Craig Riddell, and Paul M. Romer (1998). "Wages, Skills, and Technology in the United States and Canada". NBER Working Paper.

Oosterbeek, Hessel and Dinand Webbink (2007). “Wage effects of an extra year of basic vocational education”. In: *Economics of Education Review* 26.4, pp. 408–419.

Oreopoulos, Philip (2006a). “Estimating Average and Local Average Treatment Effects of Education when Compulsory Schooling Laws Really Matter”. In: *American Economic Review* 96.1, 152–175.

— (2006b). “The Compelling Effects of Compulsory Schooling: Evidence from Canada”. In: *The Canadian Journal of Economics / Revue canadienne d’Economique* 39.1, pp. 22–52.

Oreopoulos, Philip and Kjell G. Salvanes (2011). “Priceless: The Nonpecuniary Benefits of Schooling”. In: *The Journal of Economic Perspectives* 25.1, pp. 159–184.

Oyelere, Ruth Uwaifo (2010). “Africa’s education enigma? The Nigerian story”. In: *Journal of Development Economics* 91.1, pp. 128–139.

Patrinos, Harry Anthony, George Psacharopoulos, and Aysit Tansel (2020). “Private and Social Returns to Investment in Education: the Case of Turkey with Alternative Methods”. In: *Applied Economics* 54.14, pp. 1–22.

Patrinos, Harry Anthony and Chris Sakellariou (2005). “Schooling and Labor Market Impacts of a Natural Policy Experiment”. In: *Labour* 19.4, pp. 705–719.

Piketty, Thomas, Emmanuel Saez, and Gabriel Zucman (2018). “Distributional National Accounts: Methods and Estimates for the United States”. In: *The Quarterly Journal of Economics* 133.2, pp. 553–609.

Piketty, Thomas, Li Yang, and Gabriel Zucman (2019). “Capital Accumulation, Private Property, and Rising Inequality in China, 1978-2015”. In: *American Economic Review* 109.7, pp. 2469–2496.

Pischke, Jörn-Steffen (2007). “The Impact of Length of the School Year on Student Performance and Earnings: Evidence From the German Short School Years”. In: *The Economic Journal* 117.1, pp. 1216–1242.

Pischke, Jörn-Steffen and Till von Wachter (2008). “Zero Returns to Compulsory Schooling in Germany: Evidence and Interpretation”. In: *The Review of Economics and Statistics* 90.3, pp. 592–598.

Portugal, Pedro, Hugo Reis, Paulo Guimarães, and Ana Rute Cardoso (forthcoming). “What Lies behind the Returns to Schooling: The Role of Labor Market Sorting and Worker Heterogeneity”. In: *The Review of Economics and Statistics*.

Powdthavee, Nattavudh, Warn N. Lekfuangfu, and Mark Wooden (2013). “Assessing the Effect of Schooling on Earnings Using a Social Experiment”. IZA Working Paper.

Roodman, David (2022). “Schooling and Labor Market Consequences of School Construction in Indonesia: Comment”. Working Paper.

Rossi, Federico (2022). “The Relative Efficiency of Skilled Labor across Countries: Measurement and Interpretation”. In: *American Economic Review* 112.1, pp. 235–266.

Sakellariou, Chris (2006). “Education policy reform, local average treatment effect and returns to schooling from instrumental variables in the Philippines”. In: *Applied Economics* 38.4, pp. 473–481.

Schoellman, Todd (2012). “Education Quality and Development Accounting”. In: *The Review of Economic Studies* 79.1, 388–417.

Spohr, Chris A. (2003). “Formal schooling and workforce participation in a rapidly developing economy: evidence from compulsory junior high school in Taiwan”. In: *Journal of Development Economics* 70.1, pp. 291–327.

Stephens, Melvin Jr. and Dou-Yan Yang (2014). “Compulsory Education and the Benefits of Schooling”. In: *American Economic Review* 104.6, pp. 1777–1792.

Torun, Huzeyfe (2018). “Compulsory Schooling and Early Labor Market Outcomes in a Middle-Income Country”. In: *Journal of Labor Research* 39.1, 277–305.

Vieira, José A.C. (1999). “Returns to education in Portugal”. In: *Labour Economics* 6.1, 535–541.

Vu, Khoa and Tu-Anh Vu-Thanh (2022). “Higher Education Expansion, Labor Market, and Firm Productivity in Vietnam”. Working Paper.

Zhang, Junchao (2020). “Estimates of the returns to schooling in Taiwan: evidence from a regression discontinuity design”. In: *Applied Economics Letters* 27.7, pp. 1–7.

Zimmerman, Seth D. (2014). “The Returns to College Admission for Academically Marginal Students”. In: *Journal of Labor Economics* 32.4, pp. 711–754.