

INCOME INEQUALITY, EDUCATION AND SKILL-BIASED TECHNOLOGICAL
CHANGE

by Simin Xiao

(7557217)

Major Paper presented to the
Department of Economics of the University of Ottawa
in partial fulfillment of the requirements of the M.A. Degree
Supervisor: Professor Marcel Mérette

ECO 6999

Ottawa, Ontario
April 2019

Abstract. This paper provides an empirical analysis of the relationship among income inequality, education inequality and skill-biased technological change (SBTC thereafter). If education expansion reduces income inequality, SBTC increases it as it favors skilled (more educated) over unskilled labor. My paper develops a model that takes into consideration the skill-biased technological progress observed since 1990. My empirical results are consistent with the hypothesis that SBTC counteracts the education compression effect on income inequality to different extents over the past decades.

1. Introduction

During the last few decades in most of the countries worldwide, economic levels and income inequality have increased significantly. These trends are largely characterized by increasing inequality within education groups and industries. In addition, rising economic growth has occurred simultaneously with educational and technical development. In an aim to reduce income inequality, some of these countries have invested heavily in compulsory education, so that the lower end of the education distribution shifted significantly over the years. With most people now finishing primary education, the difference in education between skilled and unskilled labor is no longer as large, and the education distribution in these countries are becoming increasingly compressed. Since the 1990s, the discussion on the rate of return to education has been sparked by micro labor research and the macro growth literature (Levison et al. 1991, Krueger and Lindahl 2001, De Gregorio and Lee 2002). They estimate the monetary return of schooling and the relationship between educational attainment and GDP growth rate. Long-term economic growth generates the financial resources governments need to improve the well-being of their citizens. One puzzle is the following paradox: Economic growth does not always translate into human development, especially when it is accompanied by rising income inequality. Evidence in the OECD area shows that when income inequality rises, economic growth falls (Cingano, 2014). According to his research, one reason that may explain slow growth in some developing countries is that they are less able to invest in their education.

It has been argued that investment in human capital, especially in the form of schooling years, is essential for countries and individuals to achieve greater economic benefits (Becker 1964; Fields 1980). Previous empirical analysis tends to support the theoretical prediction that education has a significant effect on income inequality. Gregorio and Lee (2002) report their empirical results on

the relationship between education and income distribution in panel data covering a broad range of countries for the period between 1960 and 1990. They found that development in educational attainment and distribution reduce income inequality. The effect of education on income distribution has been discussed by a great number of authors in empirical work. Breen and Chung (2015) suggest that the change to education would take many years through a large section of the population. They conclude that educational upgrading may not reduce inequality. There has also been a debate in the literature about the quality of different data sources (Cohen and Soto 2007; Barro and Lee 2013).

Therefore, in this paper, I propose that in examining a cross-country regression income Gini on education Gini, one should control for economic growth. For example, in comparing countries with different levels of education inequality, one should search for countries that have experienced similar economic growth rates. In this paper, I first document the evolution of education and income over time, as well as their institutional causes for three very different countries — Brazil, the United States, and China. The Kuznets curve proposes that along with economic development, one will first observe an increase in income inequality, and then a decrease will follow. I plot the time series of income and education for these three countries to check whether they agree with the alleged facts. For further analysis, I combine an updated Barro-Lee data set to calculate its education Gini for a representative set of countries in the world. Merging with income Gini and GDP growth rate from Penn World Tables, I run a panel data regression of income Gini on education Gini, controlling for GDP growth rate and country-fixed effects. The effect of education compression to income inequality is counteracted by technology growth. Technology growth is typically skill-biased so that it favors skilled labor and increases income inequality. One prominent example is the adoption of computerized production in which only laborers with sufficient

computer skills can benefit from. In the case of the United States, given that education distribution does not change significantly over time, skill-biased technical change has increased income inequality. Generally, since different countries experience different levels of growth, the strength of Skill-Biased Technology Change (SBTC) would vary across countries; thus, counteract the education compression effect to different extents.

The next section reviews the previous theoretical and empirical literature. Section 3 explains the methodology and basic model. Section 4 describes the data. Section 5 reports the estimation results. The final section concludes, identifies caveats and makes some suggestions for further research.

2. Literature Review

The model used in this paper is largely motivated by Kuznets hypothesis and Mincer's human capital model. I thus start referring below to some of the important theoretical literature on economic growth and income distribution, including the contribution of Kuznets and Mincer. Then, I emphasize the quantitative results obtained on this topic as my contribution is also empirical.

2.1 Theoretical Review

In the 1950s and 1960s, Simon Kuznets hypothesized that as an economy develops, the overall economic inequality of society first increases and then decreases, which is illustrated by the inverted U-shape of the Kuznets curve. According to Kuznets (1955), there are two main reasons for increasing inequality in the distribution of income. First, the cumulative effect of savings concentration only exists in upper-income groups. Second, the industrial structure changes in developed countries. Kuznets assumed the income distribution of the total population is a

combination of income distribution of the rural and of the urban populations. Developed countries witnessed industrialization and urbanization in their process of economic growth. He concludes that the widening income inequality is due to the shift from the agricultural to nonagricultural sectors. However, this theory has its limitations. The primary criticism of Kuznets's hypothesis is that the inverted U-shape of the Kuznets curve begins to diminish when more countries are included. Other critics have shown that some countries that underwent rapid economic growth did not necessarily follow Kuznets's hypothesized pattern (Barro, 2000). Kuznets curve cannot explain the economic progressing of an individual country. Kuznets himself emphasized the lack of data for underdeveloped countries. In this study, I intend to discuss the relationship between income inequality and economic growth. My regression results prove that cross-country Kuznets curve does exist. I will also explain the impact of educational distribution and compare the developed and developing countries over recent decades.

The human capital model is the basis of a neo-classical analysis of the labor market, education and economic growth. The positive correlation between education and income is a well-established fact in the theory of human capital. Human capital can be applied to the returns to an individual from his/her education. An investment in human capital will usually increase earnings. One way of investing in human capital and becoming more productive is to improve the knowledge and skills of workers through school training (Becker, 1975). Although Becker's original analysis focused on the private benefits to graduates, economists who followed his theory expanded their studies to the broader social welfare. This is a powerful idea, which explains why countries with a higher growth rate have invested more heavily in education. Mincer, almost at the same time as Becker, also believed that higher education, as both a public and private investment decision, leads to economic growth. In the basic Mincer model, wages are determined by the years of education

and the years of experience. The Mincer equation (1974), which is an individual-level relationship between education and income, implies that a reduction in education inequality should reduce income inequality. In Mincer's equation, wages depend only on schooling and experience. When I apply the basic Mincer model to the newest data, the causes of rising income inequality are not only education, but also technological change. In a globalizing world economy, technological change has been affecting economic growth and inter-country income inequality. The effect of technology on economic growth and the labor market has been a core concern for a long time. Technical change is defined as a shift in the production function with different factor inputs. The traditional measure of technological change, introduced by Solow (1957), is aggregate total factor productivity. Solow treats technology as a neutral factor. Other research prefers that technology is skill-biased. Recent shifts in technology, for example, the information technology revolution, induce an increase in the relative productivity of skilled labor. According to Tinbergen (1974), inequality is the outcome of a race between education and technology. A large number of economic models in the literature provides a foundation for skill-biased technological change hypothesis (Acemoglu, 1998; Galor and Moav, 2000; Autor, Levy and Murnane, 2003). They reached a consensus that technical change alters job skill demands and an increase in technological progress widens the wage inequality. According to Galor and Moav (2000), technical development increases the average wage of skilled workers and decreases the average wages of unskilled workers. Moreover, they find a positive relationship between education and technological transition.

2.2 Empirical Reviews

Studies by Kuznets have shown that income inequality in developed countries had decreased throughout the twentieth century. Schultz (1968) investigated secular and cyclical variables (the

rate of change in price, the rate of change in real per capita income, and the unemployment rate and time trend) in the income concentration model. He found that income inequality decreased markedly in the Netherlands during the postwar period. His empirical evidence of the Netherlands proves the studies of Kuznets. Before and after World War II, the Netherlands had a downward trend in income inequality. Deininger and Squire (1998) use cross-country data on income and asset distribution. They found that there was a robust negative relationship between initial inequality in asset distribution and long-term growth, but failed to confirm a cross-country Kuznets curve. Is rising inequality good or bad for growth? Partridge (1997) suggests that states with higher Gini coefficients at the beginning do experience subsequent economic growth. The overall relationship between inequality and economic growth is negative for developing countries, not for advanced economies. Freeman (2011) is one of the economists who believe that inequality has a positive effect on growth up to a point. Rising inequality only hampers growth after that point. Barro (2000) does not agree, and he shows that high levels of inequality undermine growth in relatively poor countries but encourage growth in richer countries. Anand and Segal (2008) point out that the choice between survey means can be important in measuring global inequality. They conclude that the direction of change in global inequality depends on the estimation methods and datasets. Most of the empirical studies use the Gini coefficient as an indicator of inequality. Warner et al. (2014) compute both the Gini and Theil inequality measurements and find a declining inequality at the global level. But when they omit China, inequality in Asia and globally increases. They conclude that China's economic growth contributes mainly to the decline in global inequality. Gini coefficient is a traditional measure of inequality. It is the most widely cited measurement. Cross-country research has been hindered by the limitations of the previous inequality datasets (Solt, 2019). A database such as Standardized World Income Inequality

Database (SWIID) maximizes the comparability of income inequality data while maintaining the broad coverage of countries over time.

Some empirical evidence estimates the effect of education on economic growth. For example, some developing economies have experienced rapid growth with relatively low income inequality since the 1960s. Levison et al. (1990) used household survey data from Brazil to show that schooling improved income distribution from 1967 to 1986. They predicted that improvements in educational attainment should continue to have an impact on economic growth. Krueger and Lindahl (2001) reviewed some major studies on Mincer human capital function and compared different empirical analyses on the return on education. They explained the inconsistency between the micro and macro literature on the return on education. They believed that education had a larger effect on economic growth in the cross-country regressions than in the within-country regressions. De Gregorio and Lee (2002) presented empirical evidence on how higher educational attainment improves income distribution in panel data covering 146 countries. They found that equal distribution of education reduces income inequality. Teulings and Rens (2008) reconciled the private and public return on education in the cross-country panel data on inequality and GDP. They also proved the positive effect of education on GDP growth. Their empirical results stated that the long-run social return on education was much higher than the private return. Drawing upon the findings of 64 econometric studies, Abdullah et al. (2015) found that education appears to have the most significant effect on the two tails of income distribution, reducing the income share of the rich and increasing the income share of the poor. It also appears that education has a relatively more significant impact on increasing the income share of the poor than on reducing the income share of the rich. Breen and Chung (2015) use data from NLSY79 (National Longitudinal Survey of Youth 1997) and carry out a three-level decomposition of total inequality into within-person,

between-person, and between-education parts. They find that the between-education contribution to inequality is small and suggests that educational policy is likely to have only a minor impact on income inequality. Coady and Dizioli (2017) believe the effect of education on income inequality is not always significant, but it is significantly negative for the younger cohorts.

There has not been a clear-cut definition on an appropriate proxy for human capital. In early studies, the number of years of schooling was the most common indicator to measure human capital (Barro and Lee, 1993). Measuring the quality of education is difficult; thus the majority of the literature to investigate the relationship between education and income distribution employs measures of the quantity of schooling. A famous dataset on educational attainment is the Barro-Lee dataset. Their dataset includes the average years of schooling as the educational attainment for 146 countries in 5-year intervals from 1950 to 2010 for the total population aged 15 and over. Cohen and Soto (2007) focus on the difference between their dataset for years of schooling and Barro-Lee's (2001) dataset and find some implausible results in the Barro-Lee (2001) series. However, Barro and Lee improved their dataset and showed a comparison with estimations by Cohen and Soto (2007). The new Barro-Lee dataset (2018) displays less dispersion than that of Cohen and Soto (2007) among levels for all sample groups, except for that of advanced countries in 1960. Barro and Lee's new estimates of educational attainment can provide a reasonable proxy for the stock of schooling capital for a broad group of countries, although they still do not account for heterogeneity in the quality of schooling across countries. However, a comparative study of the quality of education is difficult to achieve based on current data. The 2018 Barro-Lee dataset is more useful than the previous one for a variety of empirical work because it provides data for a broad group of countries and updated estimates.

Education by itself, if not by influencing other factors, may not have a significant impact on inequality. Space does not permit a discussion on the demographic, political and social considerations that could be used to explain and offset any declines in income inequality. Here I am most interested in the concept of skill-biased technological change. Without diminishing the linkage between learning and development, education has continuously been at the core of individual and economic growth.

Some observations can be made about technological progress. In the case of the United States, given that the education distribution does not change significantly over time, skill-biased technological changes have increased income inequality (Daron, 1998). Acemoglu (1998) suggested that the rapid increase in the proportion of skilled labor in the United States labor force in the 1970s caused an increase in inequality. Other economists observed ability-biased technological transition patterns in the United States and other advanced countries. Galor and Moav (2000) argued that wage inequality decreases when the rate of technological progress increases, because of the increasing return of skills. Most of the recent empirical work refers to the impact of computerization. Autor, Levy, and Murnane (2003) estimated that there was a relative demand shift favoring the skilled worker (college labor) between 1970 and 1998. Goldin and Katz (2009) provide a detailed overview of the United States to discuss the relationship between the relative supply of skilled labor due to education and the relative demand for skilled labor driven by technology. In periods when education races ahead, faster than technology, the relative wages of skilled to unskilled labor fall, and economic inequality declines. However, if the increases in technology speed up, then inequality rises as the relative wages of skilled to unskilled labor rise. Generally, since different countries experience different levels of growth, the strength of skill-biased technological change (SBTC) would vary across countries and hence counteract the

education compression effect to different extents. In the most recent World Bank Global Economic Prospects Book (2018), a shift in the skill composition of the global labor force will have significant consequences on global income inequality. Specifically, a more educated labor force from emerging market and developing economies will likely reduce inequality between countries. It would also diminish inequality within countries, especially in emerging markets and developing economies.

When evaluating the SBTC, several indicators have been used in the previous literature. For instance, Loo and Soete (1999) used R&D (which is generally believed to be an acceptable proxy of the state of technology) expenditures. Autor et al. (2003) used computer usage, and Gray (2013) used the occupation structure. These empirical works used industry-level data and analyzed data within countries; however, there is no direct measurement of SBTC across countries. We follow the economic growth theory that the SBTC effect should be stronger in a region with a higher GDP growth rate. SBTC is an increase in production technology that favors skilled over unskilled labor. The effect of SBTC becomes stronger if the GDP growth rate is larger. We will use the interaction between education Gini and GDP growth rates; it is available in the database for the entire period of our analysis and all the countries.

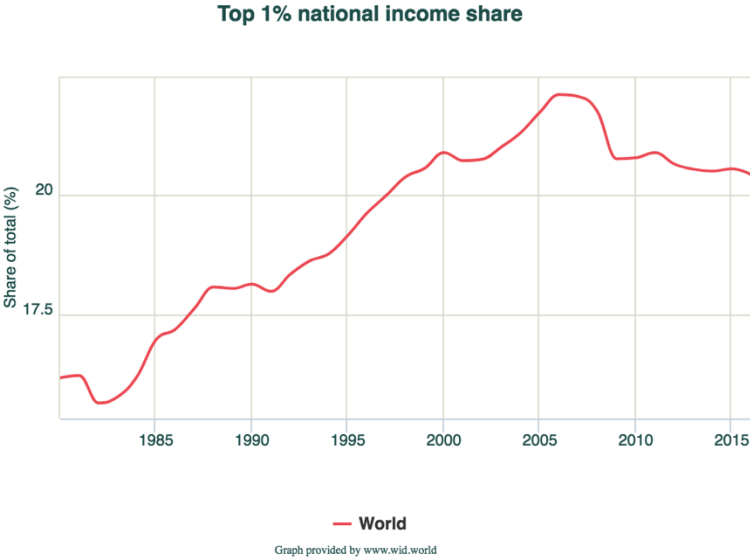
The research on educational inequality plays an essential role in making social policies. It is thus important to continue to go deeper in the analysis in order to improve social policies. I intend to contribute to the literature on this topic by taking into consideration SBTC. Previous empirical research investigated the SBTC hypothesis within a country or industry. This paper introduces a new data-set of educational inequality of 146 countries, from 1950 to 2010, and presents a Gini index of education by 5-year intervals and for a broad panel. I use the Gini index of education as a measure of the distribution of years of schooling. Second, I review the evidence in favor of the

SBTC hypothesis using updated panel data and compare the trends among countries with different GDP growth rates. The results indicate the existence of SBTC in developing countries, which is a major limitation for previous empirical evidence.

3. Methodology

It is acknowledged that income inequality in the world rose rapidly since the late 1980s. The rise in inequality is often represented by the income share of the people belonging to the top 1% in terms of level of income.

FIGURE 1 Top 1% income shares across the world, 1980-2016: Rising inequality in the world between 1985-2010



As shown in Figure 1, the global top 1% income share increased from 17% in 1985 to 22.1% in 2007 in the world. The World Inequality Report 2018 said the global top 1% earners has captured twice as much of that growth as the 50% poorest individuals since 1980s. Many economies underwent sharp technological transformation since the 1990s, suggesting the possibility that technology absorption may have accelerated during the past decades.

The skill-biased technological change (SBTC) hypothesis argues that increased demand for skilled workers has been largely driven by the kinds of new technologies that are permeating into modern workplaces. The critical idea is that these new technologies lead not only to higher productivity, but also favor more educated workers. At the same time workers who do not possess the appropriate skills to operate the new technologies face decreased demand. As such, the wages and employment of the more skilled rise relative to their less skilled counterparts.

To study the phenomenon of skill-biased technological change, one would like information on occupation of employed person and worker mobility. Unfortunately, information on individual occupation is not widely available in labor force surveys, survey-based evidence on worker mobility is not enough, and panel data of SBTC for cross-country tests is nonexistent. As there is no direct measurement of SBTC across countries, I have to rely on an indirect way to capture the impact of SBTC on income distribution. To do that I follow the assumption that SBTC effects should be stronger in a region experiencing higher GDP growth. SBTC is an increase in the production technology that favors skilled over unskilled labor. SBTC is more likely to be present when GDP growth rate is larger. Consequently, the interaction between education Gini and GDP growth rate can be used to approximate the impact of SBTC.

3.1 A Framework of Mincer Model and Skill-Biased Technological Change Theory

The famous Kuznets Curve shows that income distribution would follow an inverted "U" shape as it rises and then falls again as an economy develops. To illustrate this, Park (1996) has suggested the following expression:

$$gini = c_0 + c_1 \ln y + c_2 \ln^2 y + u \quad (1)$$

where *gini* is the Gini index, one classification of income inequality. Such a coefficient ranks how income is distributed in a nation on a scale from 0 (perfect equality) to 1 (perfect inequality). The

variable $\ln y$ is shorthand for the natural logarithm of GDP per capita. The variable $\ln^2 y$ is the square of logarithm of GDP per capita.

In the Mincer wage equation, the log wage earnings are considered proportional to schooling and experience. An empirical representation of human capital theory would take this form:

$$W_i = \text{constant} + \gamma_s S + \gamma_e E \quad (2)$$

where i refers to individual i , W to wage, S to levels of schooling, and E to experience.

The Mincer equation was inspired by equation (2). Mincer emphasizes life cycle dynamics of earnings and examines the relationship between observed earnings, potential earnings and human capital investment. He assumes a linearly declining rate of post-school human capital investment and post-school investment is a function of work experience and retirement age. Under these assumptions, the Mincer equation involves fitting a log-wages function using years of schooling, years of labor market experience and its square as independent variables. It can be written as the following expression:

$$\ln W_i = \alpha + \beta S_i + \gamma E_i + \delta E_i^2 + \varepsilon_i \quad (3)$$

where S is years of schooling and E is work experience. E^2 is experience squared, and ε is a random disturbance term capturing unobserved characteristics. In this function, the β coefficient on years of schooling can be interpreted as the average rate of return (or the percentage change in wages) to an additional year of schooling, regardless of the educational level. The term E^2 captures the possibility of a non-linear relationship between earnings and experience. A non-linear relationship reflects that each unit change in the experience variable will not always bring about the same change in the earnings variable.

Based on traditional models of human capital theory for the relationship between the levels of earnings and years of schooling, De Gregorio and Lee (2002) extend the empirical relationship by focusing on the distribution of income. Their main empirical equation looks like this:

$$\text{Var}(\ln y_s) = \bar{r}^2 \text{Var}(s) + \bar{s}^2 \text{Var}(r) + 2\bar{r}\bar{s} \text{Cov}(r, s) + \text{Var}(\varepsilon) \quad (4)$$

This equation suggests a relationship between educational inequality $\text{Var}(s)$ and income inequality $\text{Var}(\ln y_s)$. If the rate of return r and years of schooling s are independent $\text{Cov}(r, s) = 0$, an increase in the level of schooling s will lead unambiguously to a greater income inequality. However, the total effect of education improvement on income inequality is ambiguous if the covariance between the years of schooling s and the rate of return r is negative.

Now, we consider the aggregate production function of three inputs and time, $Y = F(K, S, L, T)$, where K is capital, S is skilled labor, L is unskilled labor, T is time. The definition of the bias of technological change is the rate at which the elasticity of output with respect to any factor $f \in (K, S, L)$, $\frac{\partial \ln Y}{\partial \ln f}$, changes with time, $\frac{\partial^2 \ln Y}{\partial \ln f \partial \ln T} \equiv \gamma_f$. The previous literature defines SBTC as a shift in the production technology that favors skilled over unskilled labor by increasing its relative productivity and, therefore, its relative demand ($\frac{\partial \ln Y}{\partial \ln S}$ grows at a faster rate than $\frac{\partial \ln Y}{\partial \ln L}$).

Following De Gregorio and Lee (2002), we represent the distribution of income as:

$$gini = c_0 + c_1 \text{edugini} + c_2 \text{gdpgr} + c_3 \text{edugini} * \text{gdpgr} + u \quad (5)$$

$c_1 + c_3 \text{edugini}$ tells us the marginal effect of educational Gini on income Gini in this regression.

If $c_3 < 0$, it means that the marginal effect of education Gini on income Gini is negatively depended on SBTC. We can expect a positive c_2 while a negative interaction term. Without a direct measurement of SBTC across the country, our assumption and proxy are not ideal but feasible. In the next section we look at the relationship among income inequality, the education inequality and economic growth. We focus on the issue whether countries with higher levels of development and

stronger SBTC effects, or with less dispersion of education, have a more equal income distribution. We estimate the following regression:

$$gini = c_0 + c_1edugini + c_2gdpgr+c_3inter + u \quad (6)$$

where the term *inter*, which stands for the interaction term. As argued, the strength of SBTC should relate to GDP growth rate. For a country or region with higher growth, its SBTC impact should be stronger. I investigate the hypothesis that skill-biased technological change did in fact arrive in the 1990s using panel data merged by Barro-Lee (2018) and Penn World Table 9.0 (PWT). The PWT data confirm the 1990s showed generally rising demand for skills with variation across countries. Our study uses a fixed effects model to address the problem of omitted variable bias that might vary from country to country but is constant over time. We assume that unobservable factors that might simultaneously affect the LHS and RHS of the regression are time-invariant. The fixed effects regression will eliminate omitted variable bias.

4. Data and Descriptions

4.1 Data on Education

Educational Gini is calculated from Barro-Lee (2018), which is an updated dataset created in 2001. The Gini coefficient is a statistical measure of dispersion developed by the Italian statistician Corrado Gini in 1912. A Gini coefficient of zero means perfect equality. Higher is the coefficient, higher is the degree of inequality. A coefficient of one means maximal inequality which means that all values (income, consumption) belong to one person only. Barro-Lee Educational Attainment Datasets (2010, 2013) have been widely cited in economic journals. Barro-Lee dataset provides educational attainment data for 146 countries within 5-year intervals from 1950 to 2010

as well as information about the distribution of educational attainment of the adult population over age 15 and over age 25 by sex at seven levels of schooling. Barro and Lee (2018) have made several important changes since 2014 to the earlier versions and corrected some mistakes in the estimates for 12 countries (Finland, China, Albania, Bolivia, Cameroon, Dominican Rep., Egypt, Fiji, Ghana, Kenya, South Africa, Sweden). They include 89 census observations from the 86 countries, mostly for the years 2005 and 2010. The UNESCO Institute for Statistics provides the census data on educational attainment of the population by age and by gender. A more detailed list of these changes is presented in the appendix.

4.2 Data on Income

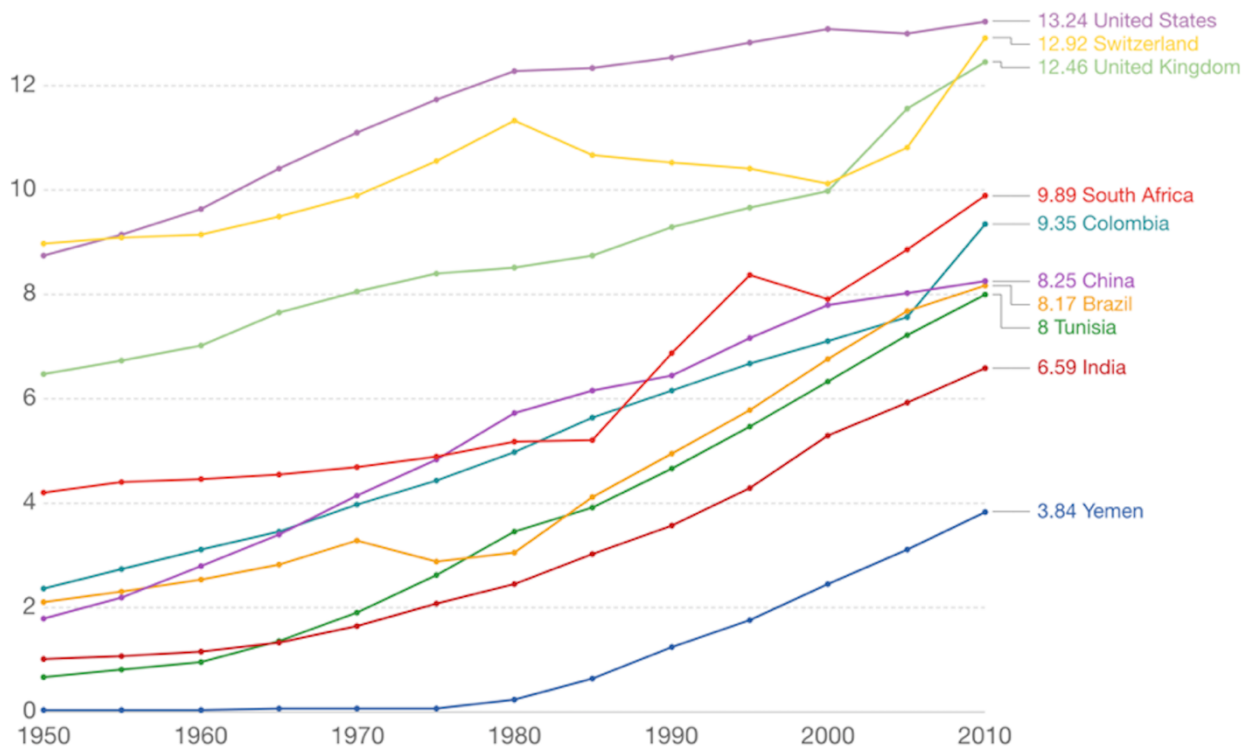
The data for income distribution are calculated from Penn World Table Version 9.0 (2016). The Penn World Table has long been used to compare living standards and explain differences across countries. PTW9.0 is the newest version and contains new and revised real national accounts data, covering 182 countries between 1950 and 2014. Feenstra, Inklaar, and Timmer (2016) explain that the changes fall into three broad categories. First, PWT9.0 adds the PPPs from ICP 2011 to the set of PPP benchmarks and shift the reference year from 2005 to 2011. The PPP and expenditure data at a detailed level are available in the so-called benchmark years of the International Comparison Program (ICP). Second, they revised and extended the National Accounts data. Third, they revised estimates of factor input data and labor cost shares. The PWT database breaks down GDP by major expenditure categories, household consumption, investment (and gross fixed capital formation), government consumption, exports, and imports (User Guide to PWT9.0). The expenditure-side real GDP is the most widely used measure for comparing relative living standards. To make the different levels fully comparable, I use expenditure-side real GDP measured in 2011 US dollars

(million) at chained Purchasing Power Parity in this paper. Therefore, the variable income Gini and GDP growth rate are computed based on PW 9.0 data.

4.3 The Evolution of Education

The world is more educated than ever before. Here we show evidence of this process of education expansion in Figure 2 by reporting cross-country estimates of average years of schooling for ten different countries.

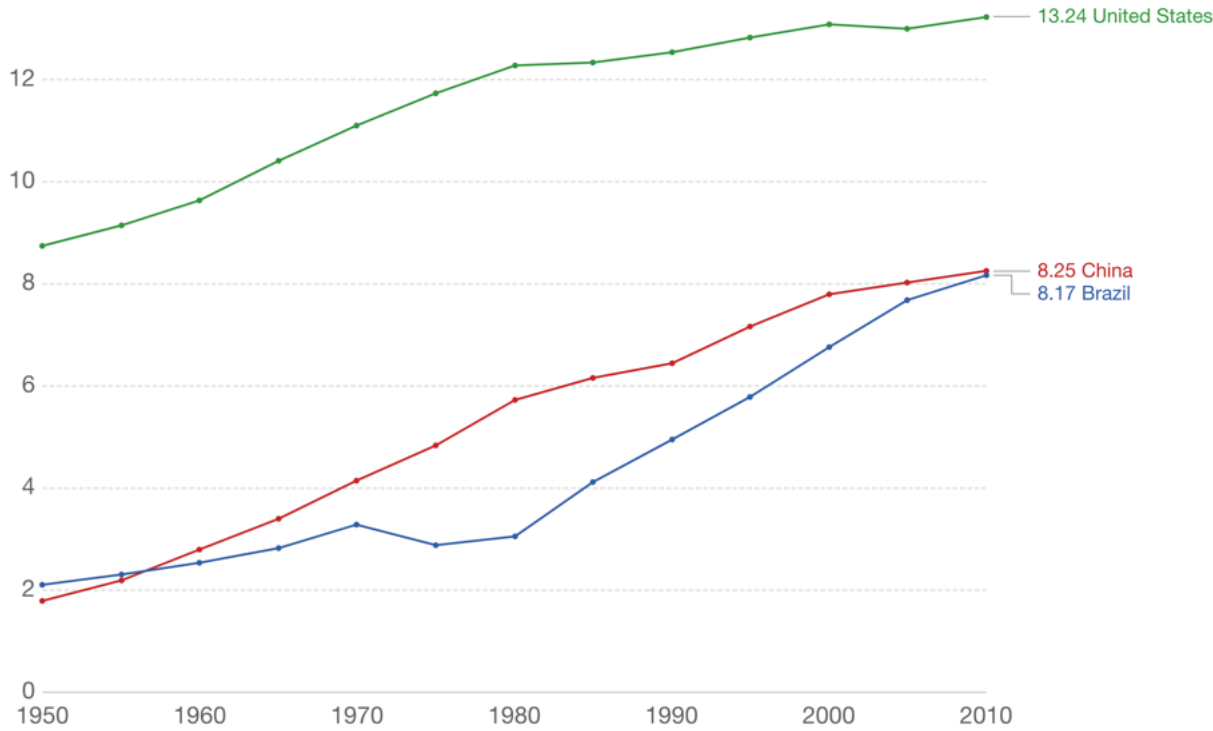
FIGURE 2 Mean years of schooling, Average number of years of total schooling across all education levels, for the population aged 15-64.



SOURCE: Barro and Lee (2018), Our World in Data

Overall, all these countries have seen a rise in the average number of years spent in school over the past five decades. The three developed countries (the United States, Switzerland, and the United Kingdom) have higher levels of educational attainment than other seven developing countries. In some countries, the increase in average years of schooling has been more substantial. For instance, Figure 3 shows trends in years of schooling for Brazil, China, and the United States during the period 1950-2010. The experience of Brazil and China shows how remarkably quickly educational attainment can increase. The mean years of schooling for both two countries increased from 2 years in 1950 to 8 years in 2010. However, the education trend of the United States has increased at a much slower pace since 1980.

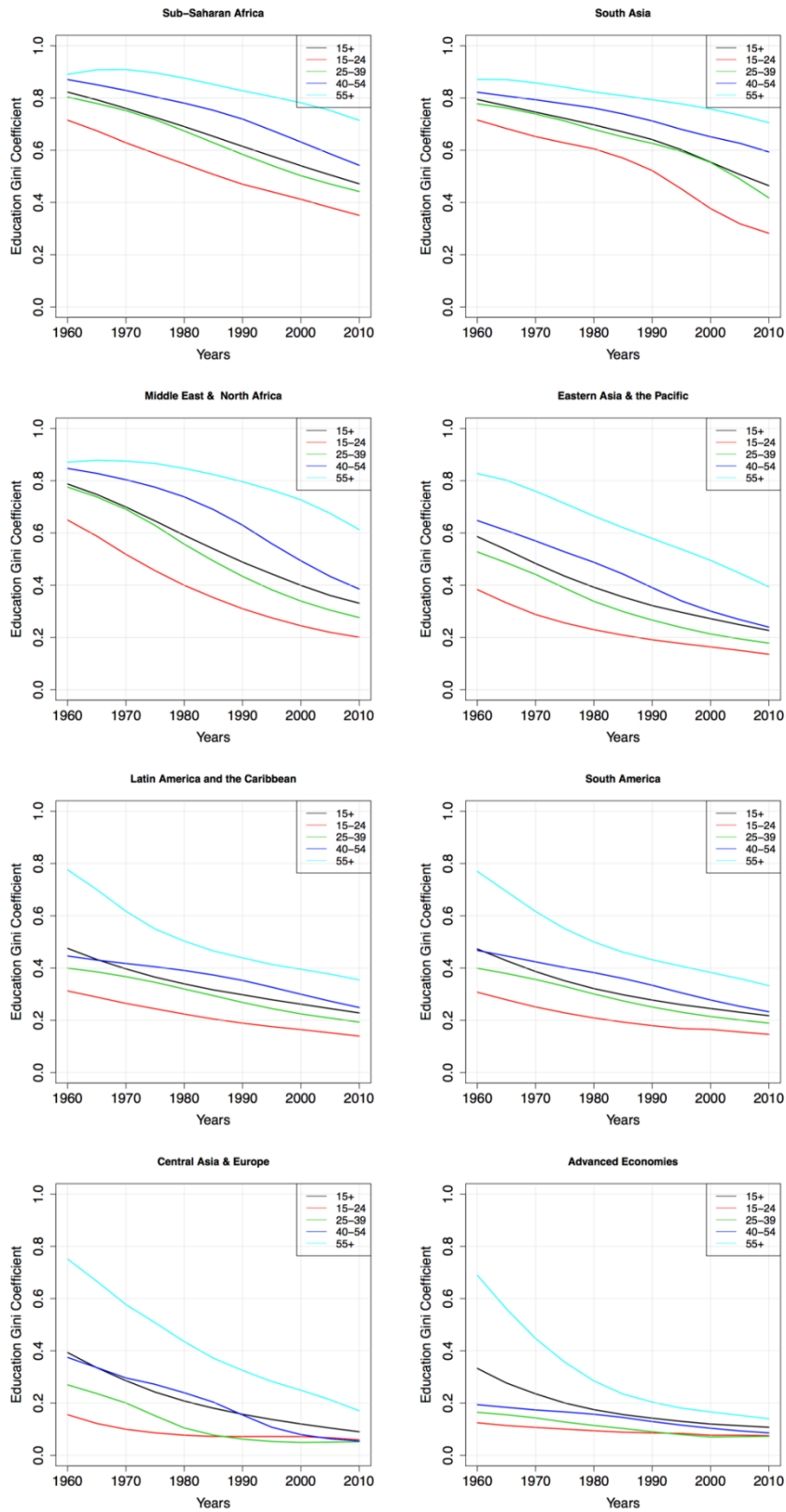
FIGURE 3 Mean years of schooling, Average number of years of total schooling across all education levels, for the population aged 15-64.



SOURCE: Barro and Lee (2018), Our World in Data

Figure 4 reports the recent evolution of inequality in educational attainment, through a series of graphs plotting changes in the Gini coefficient for eight regions of the world. The regions are defined by the World Bank (Sub-Saharan Africa, South Asia, Middle East & North Africa, East Asia & the Pacific, Latin America & the Caribbean, South America, Central Asia & Europe and Advanced Economies). The time-series chart below also shows inequality by age group for the population above 15 years old, over the period 1960 to 2010. We can see that education inequality went down every year, for all age groups and in all regions of the world. The highest levels of education Gini are observed in Sub-Saharan Africa and South Asia for all age groups. When it comes to the specific age groups, South Asia reduced the inequality most rapidly for the 15-24 age group, from 0.7 to 0.3. Sub-Saharan Africa, Middle East & North Africa and Eastern Asia & the Pacific also have experienced large improvements among younger generations. The degree of inequality is more stable for economies such as Central Asia & Europe and Advanced Economies. They have the lowest value of education Gini, around 0.1, for the younger individuals. In terms of equalizing the educational distribution for the senior population, Central Asia and Europe reduced education inequality even more rapidly for the population aged 55 and above. Its education Gini decreases from 0.8 to 0.2, over the period 1960-2010.

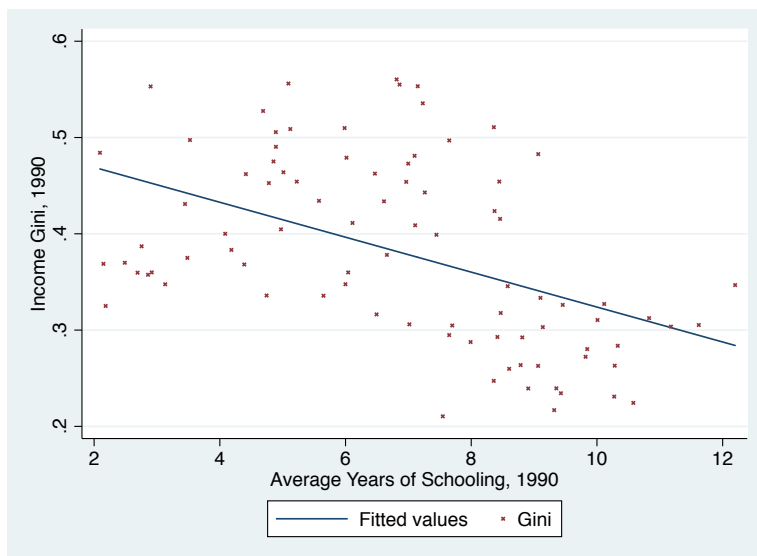
FIGURE 4 Education Gini coefficients by world region for selected age groups, 1960- 2010, Cuaresma et al. (2013)



4.4 The Evolution of Income

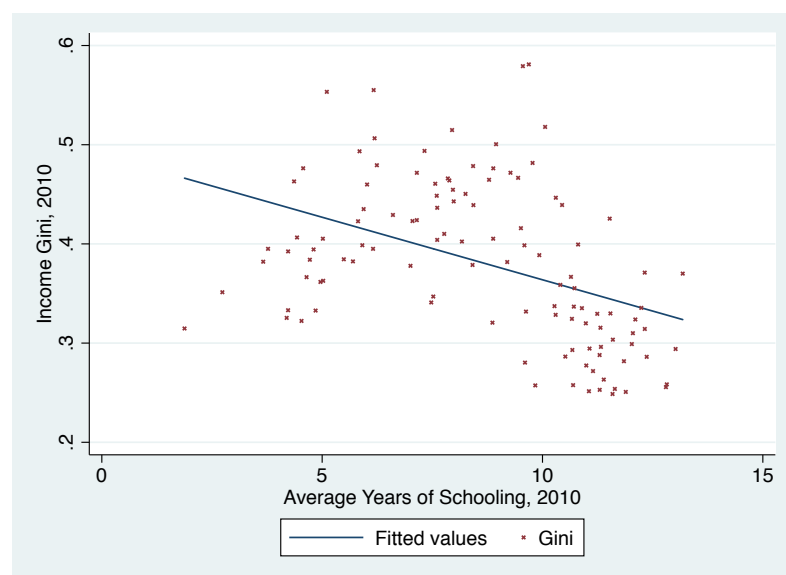
There are different ways to measure income inequality in a country. A measure that is easily and frequently used is the Gini coefficient. One big advantage of this approach is that the relevant data is readily available from the Census Bureau and other survey-based sources. Gini coefficient summarizes all the information about the distribution of income and thus facilitates easy comparisons. The Gini coefficient compares the income distribution of a population to a perfectly equal distribution. Inequality on the Gini scale is measured between 0, complete equality, and 1, complete inequality. Sometimes it can be expressed as a percentage ranging between 0 and 100. Gini coefficient allows negative values for income and wealth (owes money), unlike some other measures of inequality.

FIGURE 5 Income Distribution and Educational Attainment, World 1990



SOURCE: Author's Stata output, SWIID 6.0, Barro-Lee (2018)

FIGURE 6 Income Distribution and Educational Attainment, World 2010



SOURCE: Author's Stata output, SWIID 6.0, Barro-Lee (2018)

It will be helpful to look at the simple cross-correlation between the income and educational distribution before modeling panel data. For instance, Figure 5 and Figure 6 plot average years of schooling against the Gini coefficient with a linear regression line, in 1990 and 2010 respectively. The slope of the regression line is negative, suggesting that an increase in average years of schooling reduce income inequality. The slope is however more gentle in 2010 than 1990.

4.5 Technology, Education and Economic Growth

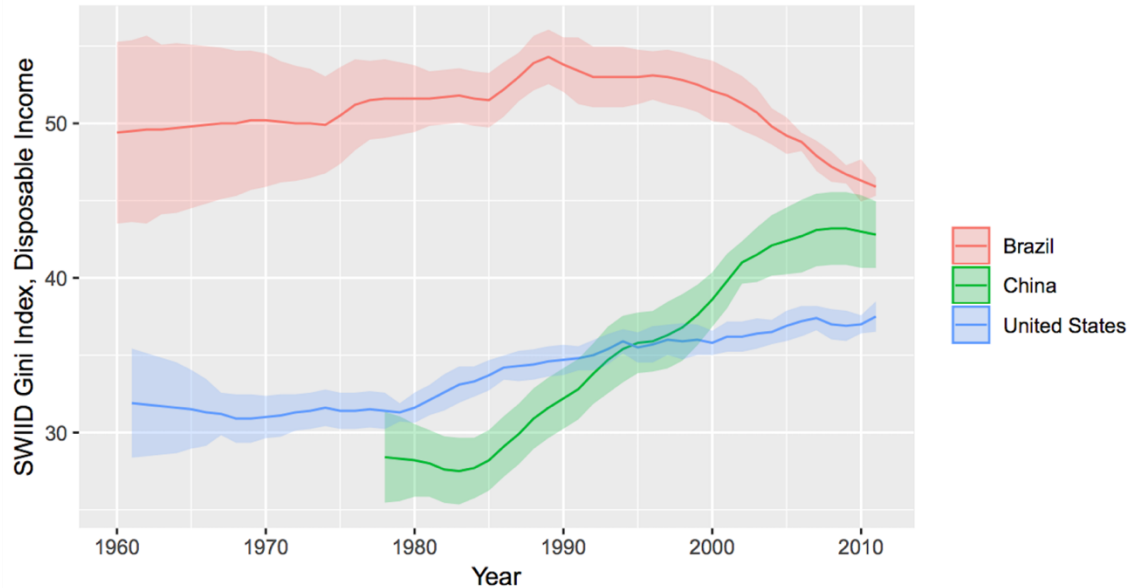
In a globalizing world economy, technological change has been affecting economic growth and inter-country income inequality. According to Tinbergen (1974) and Goldin and Katz (2009), when technology speed up, then inequality rises as the relative wages of skilled to unskilled labor rise. When education development dominates technological changes, then inequality declines.

As the Mincer equation — an individual-level relationship between education and income — implies that a reduction in education inequality should reduce income inequality. Some countries have invested heavily in compulsory education. Brazil is one prominent example where the mean

years of education have increased, and concurrently the income Gini has decreased. As a counterexample, China also experienced a significant reduction in education inequality over decades, yet its income inequality increased. In the case of the United States, given that its education distribution does not change significantly over the past two decades, its income inequality increased. As a hypothesis, the effect of education compression to income inequality is possibly counteracted by technology growth. Technology growth is typically skill-biased so that it favors skilled labor and increases income inequality. One prominent example is the adoption of computerized production, which only labor with sufficient computer skill can benefit from this technological change.

From Figure 7, we can see that income Gini of both China and United States has increased since 1990. Concurrently, Brazil’s income Gini has dramatically declined. The opposite trends in these countries suggest that education is not the sole factor affecting income distribution. This is why it is important to be able to take into consideration technological changes.

FIGURE 7 Income Gini of Brazil, China, and the United States, 1960-2010



Note: Solid lines indicate mean estimates; shaded regions indicate the associated 95% uncertainty intervals. Source: Standardized World Income Inequality Database v8.0 (Solt 2019).

4.6 Aggregate Trends in Technology

We have observed a large number of worldwide technical innovations since 1990. For example, the development of the home computer, the creation of the World Wide Web and the advancement of Wireless Communication have transformed substantially working and personal life. The most widely cited source of skill-biased technical changes (SBTC) in the 1980s and 1990s is the personal computer (PC) and related technologies, including the Internet. As late as 1989, most personal computers used Microsoft's DOS operating system. More advanced graphical interface operating systems only gained widespread use with the introduction of Microsoft's Windows 3.1 in 1990. Thus, in our estimation below, we intend to assume 1990 as the year SBTC occurs in our model.

FIGURE 8 Share of the Population Using the Internet, 1990-2017

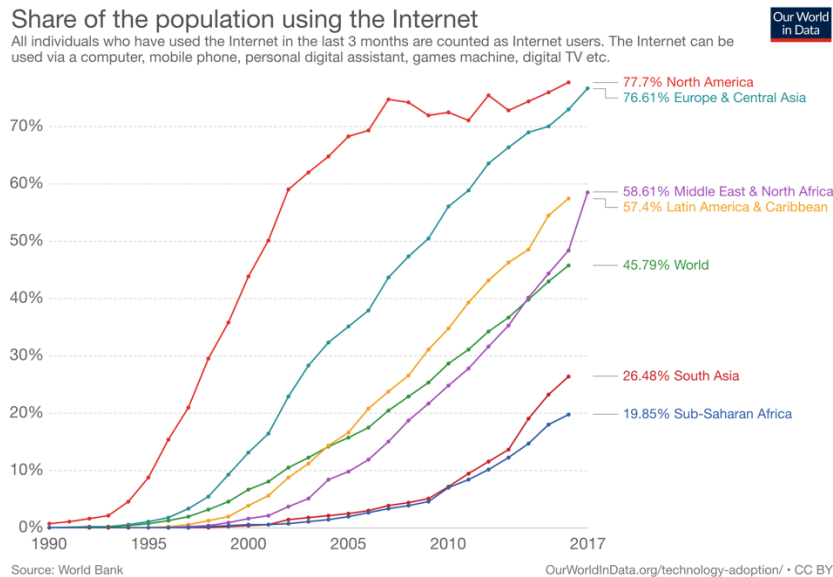


Figure 8 shows the share of the population that is accessing the internet for all countries of the world. Internet users are individuals who have used the Internet (from any location) in the last

three months. The Internet can be used via a computer, mobile phone, personal digital assistant, games machine, digital TV, etc. In richer countries, more than two-thirds of the population are typically online. Although usage rates are much lower in the developing world, they are increasing. In order to evaluate the SBTC, several indicators have been used in the literature. For instance, Loo and Soete (1999) used the R&D expenditures, Autor et al. (2003) used computer usage and Gray (2013) used the occupation structure to determine skilled vs unskilled jobs. These empirical work used industry-level data to study the SBTC issue within countries. Unfortunately, there is no statistics that can be used directly for measuring the secular SBTC effects across countries. We have to rely on an indirect way to capture the impact of SBTC on income distribution. To do that we follow the economic growth theory that bridges between the SBTC effects and GDP growth. SBTC is an increase in the production technology that favors skilled over unskilled labor. SBTC is more likely to be present when GDP growth rate is larger. For these specifications, the interaction between education Gini and GDP growth rate can be used to approximate the impact of SBTC. An advantage available in the database for the entire period of our analysis and all the countries. In the regression analysis, it is often useful to include an interaction term between different variables. To consider an interaction term, we create a new variable with the two terms multiplied together:

$$gini = c_0 + c_1edugini + c_2gdpgr + c_3edugini * gdpgr + u \quad (5)$$

In equation (5), c_1+c_3gdpgr tells us the marginal effect of educational Gini on income Gini in this regression. If $c_3 < 0$, it means that the marginal effect of education Gini on income Gini is negatively depended on SBTC. Thus, we would expect a negative interaction term. Without a direct measurement of SBTC across the country, our assumption and proxy are not ideal but reasonable.

5. Empirical Results

My analysis requires measuring income and education inequality across countries over time. I drew on information from Barro and Lee (2018) and the Penn World Table (9.0). Details of the data construction are provided in the Data Appendix. Here, I will discuss the most salient features. Before we estimate the regression between income distribution and educational inequality, we test the Kuznets hypothesis for the relationship between income level and income distribution from 1960 to 2010.

The Kuznets curve (1995) illustrates the hypothesis that the relationship between income distribution and income level is an inverted U curve. To verify this hypothesis, I add the log of income per capita and its square in the first regression to capture the inverted U shape. The output below gives us information on the coefficients of the regressors.

TABLE 1 Regression results, Full sample, 1960-2010

Source	SS	df	MS	Number of obs	=	729
Model	1.97268142	2	.986340709	F(2, 726)	=	167.89
Residual	4.26528614	726	.00587505	Prob > F	=	0.0000
Total	6.23796756	728	.008568637	R-squared	=	0.3162
				Adj R-squared	=	0.3144
				Root MSE	=	.07665

gini	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
lny	.0448703	.0083241	5.39	0.000	.0285282	.0612124
lnysq	-.0219408	.0021145	-10.38	0.000	-.0260921	-.0177895
_cons	.4078024	.0074018	55.10	0.000	.393271	.4223339

SOURCE: Author's own elaboration

I use the log of income per capita, *lny*; its square: *lnysq* as regressors. In the full sample,

coefficients of $\ln y$ and $\ln^2 y$ is 0.0449 and -0.0219 respectively. According to the results, income inequality increases when the income level goes up. The point of adding a squared to this regression is that I assume that the relationship wears off at a certain point.

$$gini = c_0 + c_1 \ln y + c_2 \ln^2 y + u \quad (1)$$

Taking the derivate with respect to $\ln y$ yields:

$$\frac{\delta gini}{\delta \ln y} = c_1 + 2c_2 \ln y$$

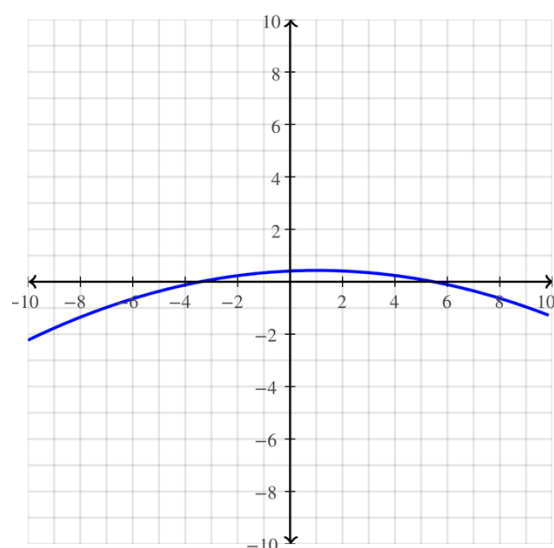
Solving this equation gives us the turning point of the relationship. This is indeed reflecting an inverse U-shape because:

$$\frac{\delta gini}{\delta \ln y} = 0.0449 - 2 * 0.0219 \ln y = 0$$

$$\ln y \approx 1.025$$

That is the point at which the relationship between income distribution and income level has its turning point. This graph shows that a Kuznets curve exists in the panel data.

FIGURE 9 Cross-country Kuznets Curve, 1960-2010



SOURCE: Author's own elaboration

In the following paragraphs, the results of the estimates performed on the full sample and on the restricted samples are reported. The software used for the estimation is STATA 15. I consider two samples of periods; in the full sample, the data for the 1960–2010 period are analyzed, and inequality data are taken from the Penn World Table (9.0) dataset. In the restricted sample, countries are considered for the 1990–2010 period. The estimation technique employed are fixed effects. The Gini coefficient has been used as an inequality measure, and five-year averages of the data have been computed to reduce the problem linked to the limited variability of the Gini coefficient across time. In the case of the fixed effect estimates on the full sample, positive and statistically significant estimated coefficient for the educational inequality measure are obtained. The value ranges from 0.0205 to 0.0361; this means that one standard deviation increase in educational inequality would be followed by an increase in the inequality of income distribution. All the other estimated coefficients, when statistically significant, take the expected sign and the robustness the test confirms, that fixed effect estimations are valid.

The first is a regression between Income Gini and Education Gini before 1990 (before SBTC occurs). Education Gini is already standardized. So, 0.036 means that one standard deviation increase in Education Gini would increase Income Gini by 0.036.

TABLE 2 Regression results, Restricted sample, 1960-1990

Source	SS	df	MS	Number of obs	=	286
Model	.402191827	7	.057455975	F(7, 278)	=	6.67
Residual	2.39363403	278	.008610194	Prob > F	=	0.0000
				R-squared	=	0.1439
				Adj R-squared	=	0.1223
Total	2.79582586	285	.009809915	Root MSE	=	.09279

gini	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
edugini_standardized	.0360832	.0053109	6.79	0.000	.0256286	.0465379
year						
1965	.0019202	.0590447	0.03	0.974	-.1143114	.1181517
1970	.0140646	.0563706	0.25	0.803	-.0969027	.125032
1975	.0208346	.0556485	0.37	0.708	-.0887113	.1303806
1980	.024053	.0551639	0.44	0.663	-.0845389	.132645
1985	.0211113	.054865	0.38	0.701	-.0868923	.129115
1990	.0232034	.0544885	0.43	0.671	-.0840592	.1304659
_cons	.3451372	.0536142	6.44	0.000	.2395959	.4506786

SOURCE: Author's own elaboration

The second is the same regression between Income Gini and Education Gini after 1990 (SBTC). As proposed, SBTC would magnify the inequality between high-skilled and low-skilled workers. Hence, a reduction in Education Gini would no longer cause Income Gini to drop as much. Indeed, we see that the coefficient drops from 0.0361 to 0.0205, which is almost half.

TABLE 3 Regression Results, Restricted sample, 1990-2010

Source	SS	df	MS	Number of obs	=	443
Model	.169762982	4	.042440745	F(4, 438)	=	5.73
Residual	3.24233889	438	.0074026	Prob > F	=	0.0002
				R-squared	=	0.0498
				Adj R-squared	=	0.0411
Total	3.41210187	442	.007719687	Root MSE	=	.08604

	gini	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
	edugini_standardized	.0205149	.0043681	4.70	0.000	.0119298 .0291
	year					
	2000	.0038174	.0116398	0.33	0.743	-.0190593 .0266941
	2005	.003445	.0115086	0.30	0.765	-.0191739 .0260639
	2010	-.0010216	.0118907	-0.09	0.932	-.0243916 .0223484
	_cons	.387087	.0083183	46.53	0.000	.3707383 .4034358

SOURCE: Author's own elaboration

The third regression is to regress Income Gini on Education Gini interacted with GDP Growth Rate. As argued, the strength of SBTC should relate to GDP growth rate. For a region with better economic performance, its SBTC effect should be more significant. So we can expect a negative interaction term. As the GDP growth rate is standardized, the interpretation is that the coefficient of 0.024 would drop by 0.006 (one-fourth) if GDP growth rate decreases by one standard deviation.

TABLE 4 Regression Results, Full sample, 1960-2010

Source	SS	df	MS	Number of obs	=	714
Model	.586977041	13	.04515208	F(13, 700)	=	5.79
Residual	5.45789898	700	.007796999	Prob > F	=	0.0000
				R-squared	=	0.0971
				Adj R-squared	=	0.0803
Total	6.04487602	713	.008478087	Root MSE	=	.0883

	gini	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
	edugini_standardized	.0247122	.0034036	7.26	0.000	.0180296 .0313948
	GDP_GrowthRate_standardized	.0125854	.003575	3.52	0.000	.0055664 .0196045
	interaction	-.0059613	.0034057	-1.75	0.080	-.0126478 .0007252
	year					
	1965	.0051578	.0562302	0.09	0.927	-.1052424 .1155579
	1970	.0172421	.05374	0.32	0.748	-.0882689 .122753
	1975	.0284133	.0530749	0.54	0.593	-.0757918 .1326183
	1980	.0269583	.0525951	0.51	0.608	-.0763049 .1302214
	1985	.0259191	.0522666	0.50	0.620	-.0766989 .1285372
	1990	.0363562	.0520169	0.70	0.485	-.0657716 .1384841
	1995	.0404577	.0517392	0.78	0.435	-.061125 .1420403
	2000	.0441661	.0517185	0.85	0.393	-.0573759 .1457082
	2005	.0432117	.0516763	0.84	0.403	-.0582474 .1446708
	2010	.0375403	.0517783	0.73	0.469	-.064119 .1391996
	_cons	.3468316	.0510354	6.80	0.000	.2466307 .4470324

SOURCE: Author's own elaboration

Given that the p-value is equal to zero, we can reject the null hypothesis at a confidence level equal to 95%. The model chosen seems thus to adequately represent the reality.

The result of these three regressions are reported in table 5:

TABLE 5 Panel regressions for income inequality

Dependent Variable	Income Gini		
	1960-1990	1990-2010	1960-2010
Education Gini	0.031 (0.006)	0.020 (0.004)	0.023 (0.003)
GDP Growth Rate	0.011 (0.008)	0.005 (0.004)	0.013 (0.003)
Interaction(SBTC)	-0.006 (0.006)	-0.388 (0.004)	-0.006 (0.003)

NOTES: The dependent variable is the Gini index for income at five year intervals from 1960 to 2010. Standard errors are reported in parentheses. Two subgroups for the period is based on my assumption of SBTC occurring in 1990. Variables measured at different scales do not contribute equally to the analysis. The education Gini and GDP growth rate have been standardized.

Table 5 reports the three regressions between income Gini and education Gini for the pre- and post-SBTC sample periods, 1960-1990 and 1990-2010 respectively. As argued in the previous sections, the strength of SBTC should relate to GDP growth rate. For a country or region with higher GDP growth rate, the effect of SBTC should be larger. Recall that skilled workers have higher education, and technological change benefits the skilled workers. According to an empirical paper of Naguib (2015), the aggregate increase in demand for skilled workers in the 1990s is evident in the fact that their proportion and relative wage increased at the same time. I investigate the hypothesis that skill-biased technological change did in fact arrive in the 1990s using panel data merged by Barro-Lee (2018) and Penn World Table 9.0 (PWT). The PWT data confirm the 1990s showed generally rising demand for skills with variation across countries. The coefficients of the interaction term are -0.388 and -0.006 for sub sample and full sample respectively. The negative values mean that the marginal effect of education Gini on income Gini is negatively depended on SBTC.

6. Conclusions

Since the early 1990s, the number of people living in extreme poverty has fallen by more than half, and average incomes in most developing countries have more than doubled. Even better, the majority of the developing countries have more equal educational distribution, millions more girls are in school and the demand for higher education continues to grow. Technological change was especially fast and industrialization became an engine of growth in developing countries.

My paper provides a contribution to the understanding of the relations among education, skilled-biased technological change and equality. The results suggest that a less unequal educational distribution is decreasing the level of income inequality, but with these results we cannot make a final conclusion that the effect is actually coming from improved education. The results presented using the fixed effects support the outcome described that a higher level of educational inequality is increasing income inequality. The SBTC plays a significant role in explaining income inequality. The effect of education compression to income inequality is possibly counteracted by technology growth. Skill-Biased Technical Change has increased the income inequality. Given that different countries experience different levels of growth, the strength of SBTC would vary cross the countries and hence counteract the education compression effect to different extents.

Education is essential to economic growth, poverty reduction, gender equality, public health, conflict resolution, and the transformation to sustainable production and consumption. The increasing availability of household and school-based surveys have made it possible to do more high quality, in-depth analyses of inequality in education both within and between countries. This paper discusses how different determinants influence income inequality. First, I deliver evidence on the Kuznets inverted U curve when only the income variables are included in the basic model. Based on unbalanced panel data from 1960 to 2010, the educational variable has a positive

relationship with income inequality. More equal educational distribution has reduced income inequality. I also studied the relationship between skill-biased technological change and income distribution. The results verify the SBTC hypothesis in the panel model. Technological progress allows for more production and stimulates economic growth. SBTC would magnify the inequality between high-skill and low-skill workers. Hence a reduction of Education Gini would no longer cause Income Gini to drop as much. A greater consensus is needed among the returns to different stages of education and SBTC effects in the international community. There are many ways to measure inequality of educational achievements. Gini index is the most commonly used but might not be the best. Also, we only investigate the population age 15 and above. It would need more clarification and tests for different subgroups in the population. There are no statistics that can be used directly for the purpose of measuring the secular SBTC effects. My model may be an oversimplified one. But I believe that it is sufficiently realistic to lend weight to the questions it poses. However, there is room for further research.

An important topic for my future research is the relations among education, fertility and equality. Education by itself, if not for influencing fertility, may not have a significant impact on inequality. First, education reduces fertility. More education makes poor people, who generally have higher fertilities, to have fewer babies. Thus, resources can be more concentrated. As a result, inequality declines. Second, China has the one-child policy, but the government relaxed this policy since 2013. The education factor had not impact on fertility in China since the 1980s. China's one-child policy provides an excellent opportunity to conduct a natural experiment on the relation between education and inequality. A basic, universal early education might reduce inequality. However, a further increase of education will probably increase inequality, and China's example might provide an exploration.

Appendix

A1. Merging datasets in Stata:

Different dataset uses different country-coding scheme. The kountry command is a Stata utility for merging cross-country data from multiple sources. This command is designed to simplify this data-management step. In particular, kountry can convert country names into “standardized names” and from one coding scheme into another. Moreover, you can “train” kountry to remember new long-country-name variations (Raciborski, 2008). However, various datasets have various coverage across countries and various country names. Also, the kountry command still has limitations. So I need to be very careful to clean the datasets before using the kountry and merge commands.

ISO 3166-1 alpha-3 codes are three-letter country codes in the ISO 3166-1 standard to represent countries and dependent territories. In order to be merge BL data and THW data, I have turned the country code ROM in BL into MDA from ISO 3166-1 alpha-3 codes for Republic of Moldova. Also, I have turned the country codes ROM, ZAR in THW into ROU and COD from ISO 3166-1 alpha-3 codes, for Romania and Democratic Republic of Congo respectively. After converting long country names into ISO3N coding scheme, there are missing codes for Cabo Verde, Congo, D.R., Czechoslovakia, Côte D'Ivoire, Kosovo, Soviet Union. According to ISO codes book, Cabo Verde, Kosovo and Soviet Union are not included in ISO3N and ISO3C coding scheme. So I have dropped these three countries and converted the other missing countries with ISO3N codes.

A2. Data:

TABLE 6 Summary of Income Data

<i>Income Distribution</i>	<i>gini</i> <i>1970</i>	<i>lny</i> <i>1970</i>	<i>gini</i> <i>1990</i>	<i>lny</i> <i>1990</i>	<i>gini</i> <i>2010</i>	<i>lny</i> <i>2010</i>
Advanced Economies						
Mean	0.287	2.707	0.291	3.193	0.302	3.670
Standard deviation	0.048	0.294	0.057	0.317	0.044	0.298
Maximum	0.378	3.162	0.464	3.781	0.423	4.432
Minimum	0.231	2.059	0.210	2.315	0.249	2.785
East Asia and the Pacific						
Mean	0.403	0.929	0.409	1.942	0.412	2.309
Standard deviation	0.066	0.662	0.069	0.822	0.055	1.058
Maximum	0.476	2.030	0.483	3.186	0.515	4.236
Minimum	0.290	-0.005	0.280	0.870	0.310	0.893
Europe and Central Asia						
Mean	0.241	1.716	0.277	2.417	0.327	2.584
Standard deviation	.	.	0.048	0.438	0.055	0.763
Maximum	0.241	1.716	0.357	3.096	0.447	3.335
Minimum	0.241	1.716	0.183	1.675	0.251	0.900
Latin America and the Caribbean						
Mean	0.461	1.710	0.469	1.767	0.459	2.216
Standard deviation	0.055	0.336	0.049	0.512	0.039	0.658
Maximum	0.514	2.160	0.553	2.831	0.553	2.945
Minimum	0.357	1.241	0.399	0.790	0.379	0.376
Middle East and North Africa						
Mean	0.480	1.323	0.385	1.964	0.374	2.963
Standard deviation	.	.	0.062	0.945	0.062	0.925
Maximum	0.480	1.323	0.462	3.246	0.472	4.800
Minimum	0.480	1.323	0.303	0.727	0.286	1.843
South Asia						
Mean	0.344	0.701	0.391	0.514	0.435	1.471
Standard deviation	0.027	0.350	0.045	0.468	0.060	0.717
Maximum	0.370	1.094	0.448	1.094	0.518	2.512
Minimum	0.316	0.423	0.348	-0.006	0.363	0.597

Sub-Saharan Africa						
Mean	0.419	0.333	0.439	0.759	0.412	0.839
Standard deviation	0.033	0.193	0.091	0.794	0.079	0.893
Maximum	0.461	0.581	0.560	2.230	0.581	2.729
Minimum	0.393	0.110	0.316	-0.214	0.315	-0.567
All countries						
Mean	0.376	1.600	0.371	2.024	0.381	2.323
Standard deviation	0.088	0.937	0.098	1.038	0.080	1.214
Maximum	0.514	3.162	0.560	3.781	0.581	4.800
Minimum	0.231	-0.005	0.183	-0.214	0.249	-0.567

SOURCE: PWT 9.0, SWIID 6.0

TABLE7 Summary of Education Data

<i>Education Distribution</i>	<i>yr_sch</i> <i>1970</i>	<i>edugini</i> <i>1970</i>	<i>yr_sch</i> <i>1990</i>	<i>edugini</i> <i>1990</i>	<i>yr_sch</i> <i>2010</i>	<i>edugini</i> <i>2010</i>
Advanced Economies						
Mean	6.938	0.215	9.116	0.212	10.951	0.157
Standard deviation	2.229	0.099	1.752	0.090	1.486	0.058
Maximum	10.777	0.461	12.199	0.439	13.183	0.280
Minimum	2.931	0.122	5.012	0.082	7.050	0.058
East Asia and the Pacific						
Mean	4.458	0.392	7.123	0.281	8.276	0.236
Standard deviation	1.607	0.084	1.985	0.106	2.463	0.089
Maximum	6.301	0.509	9.845	0.536	12.052	0.414
Minimum	2.508	0.303	4.184	0.156	4.720	0.129
Europe and Central Asia						
Mean	8.082	0.104	9.275	0.161	11.242	0.101
Standard deviation	.	.	0.915	0.043	0.790	0.038
Maximum	8.082	0.104	10.828	0.244	12.821	0.193
Minimum	8.082	0.104	7.990	0.101	9.928	0.056
Latin America and the Caribbean						
Mean	4.426	0.358	6.691	0.279	7.929	0.232
Standard deviation	1.258	0.107	1.414	0.090	1.403	0.089
Maximum	6.307	0.524	8.459	0.509	9.775	0.454
Minimum	3.276	0.199	3.525	0.106	4.569	0.053
Middle East and North Africa						
Mean	2.026	0.794	5.976	0.474	8.933	0.313
Standard deviation	.	.	2.522	0.168	2.245	0.124
Maximum	2.026	0.794	10.830	0.726	12.320	0.555
Minimum	2.026	0.794	2.858	0.205	4.960	0.162
South Asia						

Mean	3.116	0.637	4.098	0.568	6.247	0.384
Standard deviation	2.832	0.332	2.489	0.218	2.014	0.119
Maximum	6.384	0.838	8.507	0.720	10.060	0.491
Minimum	1.382	0.254	2.489	0.190	4.227	0.171
Sub-Saharan Africa						
Mean	1.354	0.728	4.253	0.476	5.600	0.389
Standard deviation	0.718	0.185	1.693	0.172	1.995	0.191
Maximum	2.275	0.918	6.860	0.799	9.690	0.777
Minimum	0.728	0.538	2.093	0.226	1.877	0.128
All countries						
Mean	4.739	0.397	7.173	0.306	8.651	0.242
Standard deviation	2.551	0.232	2.546	0.174	2.730	0.152
Maximum	10.777	0.918	12.199	0.799	13.183	0.777
Minimum	0.728	0.104	2.093	0.082	1.877	0.053

SOURCE: Barro-Lee (2018)

TABLE 8 Regional Dummies

<i>Variable</i>	<i>Description</i>
dregion1	Region = Advanced Economies
dregion2	Region = East Asia and the Pacific
dregion3	Region = Europe and Central Asia
dregion4	Region = Latin America and the Caribbean
dregion5	Region = Middle East and North Africa
dregion6	Region = South Asia
dregion7	Region = Sub-Saharan Africa

A3. Barro-Lee Data Updates

2018 June Update: In the version 2.1, there were minor mistakes in the estimates for 10 countries (Albania, Bolivia, Cameroon, Dominican Rep., Egypt, Fiji, Ghana, Kenya, South Africa, Sweden).

2016 Feb Update: In the version 2.0, there was a mistake in the estimates for China.

2014 Aug. Update: In the version 2.0, there was a mistake in the estimates for Finland in 2005 and 2010.

2014 June Update: The new version (2.0) of the Barro-Lee data set has made several important changes to the earlier version (1.3) reported in Barro and Lee (2013).

The changes affected various countries in the sample. The major changes are as follows:

- They have updated estimates of educational attainment by using the recently available UNESCO census data. They include 89 census observations from the 86 countries, mostly for the years 2005 and 2010. The census data on educational attainment of the population by age and by gender are kindly provided by the UNESCO Institute for Statistics.
- They have also collected the new census/survey observations from the UN demographic yearbook and national publications from statistics bureaus.

- They have added 126 census/survey observations in total and used them as benchmark figures for the estimation of educational attainment.
- They have corrected minor errors in the UNESCO censuses, including Korea in 1990 and Mexico in 2000.
- To maintain consistency with the observations from the other sources, they have reformulated the completion ratio of tertiary-level attainment for the census observations sourced from the UN Demographic yearbooks. The tertiary completion ratio is defined as the percentage of the number of people who have attained schooling at ISCED 5A or 6 in the number of people who have attained schooling at ISCED 5A, 5B or 6. The people who have ever enrolled in the 4th year of colleges or universities belong to the complete category.
- They have used the updated data on enrollment ratios for total and female school-aged population at each education level for 2005 and 2010.
- In this version, they have checked more carefully the consistency between the estimates of the distribution of educational attainment among total, female and male population by age group. They report the data for male population by age group together with the ones for total and female population.
- They are currently constructing estimates of historical educational attainment from 1870 to 1945 in five-year intervals. For the estimation, in this version (2.0), they have used newly compiled data on school duration data and school enrollment ratios for the years before 1950, and adopted a modified backward extrapolation technique. Accordingly, there are some changes in the estimates for the older-age population after 1950 (that is, those derived from the estimates for school-age population before 1950).

References

- Abdullah, A., H. Doucouliagos and E. Manning (2015) "Does Education Reduce Income Inequality? A Meta-Regression Analysis: Does Education Reduce Income Inequality?" *Journal of Economic Surveys* 29, 301–16
- Acemoglu, D. (1998) "Why Do New Technologies Complement Skills? Directed Technical Change and Wage Inequality," *The Quarterly Journal of Economics* 113, 1055–89
- Ales, L., M. Kurnaz and C. Sleet (2015) "Technical Change, Wage Inequality, and Taxes," *American Economic Review* 105, 3061–3101
- Anand, S., and P. Segal (2008) "What Do We Know about Global Income Inequality?" *Journal of Economic Literature* 46, 57–94
- (2015) "The Global Distribution of Income." In *Handbook of Income Distribution*, 937–79
- Autor, D.H., F. Levy and R.J. Murnane (2003) "The Skill Content of Recent Technological Change: An Empirical Exploration," *The Quarterly Journal of Economics* 118, 1279–1333
- Autor, D.H., F. Levy and R.J. Murnane (n.d.) "The Skill Content of Recent Technological Change: An Empirical Exploration," *Quarterly Journal of Economics*, 55
- Barro, R., and X. Sala-i-Martin (1995) "Technological Diffusion, Convergence, and Growth." w5151. Cambridge, MA: National Bureau of Economic Research
- Barro, R.J., and J.-W. Lee (2000) "International Data on Educational Attainment Updates and Implications." Working Paper 7911. National Bureau of Economic Research
- Becker, G.S. (1964) "Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education." SSRN Scholarly Paper ID 1496221. Rochester, NY: Social Science Research Network
- Berman, Somanathan and Tan (2005) "Is Skill-Biased Technological Change Here Yet? Evidence from Indian Manufacturing in the 1990's," *Annales d'Économie et de Statistique*, 299
- Card, D., and J.E. DiNardo (2002) "Skill Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles." Working Paper 8769. National Bureau of Economic Research
- Chotikapanich, D., W.E. Griffiths, D.S. Prasada Rao and V. Valencia (2012) "Global Income Distributions and Inequality, 1993 and 2000: Incorporating Country-Level Inequality Modeled with Beta Distributions," *Review of Economics and Statistics* 94, 52–73
- Coady, M.D., and A. Dizioli (2017) *Income Inequality and Education Revisited: Persistence, Endogeneity, and Heterogeneity*. International Monetary Fund
- Cohen, D., and M. Soto (2007) "Growth and human capital: good data, good results," *Journal of Economic Growth* 12, 51–76
- De Loo, I., and L. Soete (1999) "The Impact of Technology on Economic Growth: Some New Ideas and Empirical Considerations," Deiningering, K., and L. Squire (1998) "New ways of looking at old issues: inequality and growth." *Journal of Development Economics*, Vol. 57 _1998. 259–287
- Gregorio (2002) "Education and Income Inequality: New Evidence from Cross-Country Data," *Review of Income and Wealth*
- Feenstra, R.C., R. Inklaar and M.P. Timmer (2015) "The Next Generation of the Penn World Table," *American Economic Review* 105, 3150–82
- Fields, G.S. (1980) "Poverty, Inequality, and Development by Gary S. Fields," December.
- Forbes, K.J. (2000) "A Reassessment of the Relationship Between Inequality and Growth," *American Economic Review* 90, 869–87
- Freeman, R.B. (2011) "Globalization and Inequality," *The Oxford Handbook of Economic Inequality*, February
- Galor, O., and O. Moav (2000) "Ability-Biased Technological Transition, Wage Inequality, and Economic Growth," *The Quarterly Journal of Economics* 115, 469–97
- "Global Economic Prospects," (2019). Text/HTML available at <http://www.worldbank.org/en/publication/global-economic-prospects>. Last updated April 10, 2019
- Goldin, C., and L. Katz (2009) "The Race between Education and Technology: The Evolution of U.S. Educational Wage Differentials, 1890 to 2005."
- Gould, E.D., O. Moav and B.A. Weinberg (2000) "Precautionary Demand for Education, Inequality, and Technological Progress," *SSRN Electronic Journal*
- Gray, R. (2013) "Taking technology to task: The skill content of technological change in early twentieth century United States," *Explorations in Economic History* 50, 351–67
- Gregorio, J.D., and J. Lee (2002) "Education and Income Inequality: New Evidence from Cross-Country Data," *Review of Income and Wealth* 48, 395–416
- Heckman, J. (2018) "The Race Between Demand and Supply: Tinbergen's Pioneering Studies of Earnings Inequality." w25415. Cambridge, MA: National Bureau of Economic Research
- Khan, A.R., K. Griffin and C. Riskin (1999) "Income Distribution in Urban China During the Period of Economic Reform and Globalization," *American Economic Review* 89, 296–300
- Krueger, A.B., and M. Lindahl (2000) "Education for Growth: Why and for Whom?" Working Paper 7591. National Bureau of Economic Research
- (n.d.) "Education for Growth: Why and for Whom?" 37
- Kuznets, S. (1955) "Economic Growth and Income Inequality," *The American Economic Review* 45, 1–28
- Lam, D., and D. Levison (1991) "Declining inequality in schooling in Brazil and its effects on inequality in earnings," *Journal of Development Economics* 37, 199–225
- Meghir, C., R. Narita and J.-M. Robin (2015) "Wages and Informality in Developing Countries," *American Economic Review* 105, 1509–46

- Naguib, C. (2015) "The Relationship between Inequality and GDP Growth: an Empirical Approach." 631. LIS Working Papers. LIS Cross-National Data Center in Luxembourg
- Park, K.H. (1996) "Income Inequality and Economic Progress," *American Journal of Economics and Sociology* 55, 87–96
- Partridge, M.D. (1997) "Is Inequality Harmful for Growth? Comment," *The American Economic Review* 87, 1019–32
- Polachek, S.W. (2008) "Earnings Over the Life Cycle: The Mincer Earnings Function and Its Applications," *Foundations and Trends® in Microeconomics* 4, 165–272
- Psacharopoulos, G., and H.A. Patrinos (2018) "Returns to investment in education: a decennial review of the global literature," *Education Economics* 26, 445–58
- Sala-i-Martin, X. (2006) "The World Distribution of Income: Falling Poverty and ... Convergence, Period," *The Quarterly Journal of Economics* 121, 351–97
- Schultz, T.P. (1968) "Secular Equalization and Cyclical Behavior of Income Distribution," *The Review of Economics and Statistics* 50, 259
- Siegel, D.S. (1999) Skill-Biased Technological Change: Evidence from a Firm-Level Survey. W.E. Upjohn Institute
- Solow, R.M. (1957) "Technical Change and the Aggregate Production Function," *The Review of Economics and Statistics* 39, 312
- Solt, F. (2019) "The Standardized World Income Inequality Database, Version 8."
- Teulings, C., and T. van Rens (2008) "Education, Growth, and Income Inequality," *The Review of Economics and Statistics* 90, 89–104
- Tinbergen, J. (1974) "Substitution of Graduate by Other Labour*," *Kyklos* 27, 217–26
- "Trends in Income Inequality and its Impact on Economic Growth" (2014). OECD Social, Employment and Migration Working Papers 163
- Violante, G.L. (2002) "Technological Acceleration, Skill Transferability, and the Rise in Residual Inequality," *The Quarterly Journal of Economics* 117, 297–338
- Wail, B., S. Hanchane and A. Kamal (2011) "A New Data Set of Educational Inequality in the World, 1950-2010: Gini Index of Education by Age Group," Human Capital and Economic Opportunity Working Group
- Warner, D., D.S.P. Rao, W.E. Griffiths and D. Chotikapanich (2014) "Global Inequality; Levels and Trends, 1993–2005: How Sensitive are These to the Choice of PPPs and Real Income Measures?," *Review of Income and Wealth* 60, S281–304