Petra Sauer and Martin Zagler

(In)equality in Education and Economic Development

Article (Accepted for Publication)
(Refereed)

Original Citation:
Sauer, Petra and Zagler, Martin (2014) (In)equality in Education and Economic Development. *Review of Income and Wealth*, 60 (Suppl.). pp. 353-379. ISSN 1475-4991

(In)equality in Education and Economic Development

Petra Sauer * Martin Zagler †

July 29, 2014

Abstract

This paper investigates the relationship between the level and the distribution of education and economic development. We contribute to the literature by introducing an interaction term between the education Gini coefficient and average years of schooling. In a dynamic panel over 55 years and 134 countries we provide, on the one hand, strong evidence that more schooling is good for growth, but the coefficient is variable and substantially declining in the degree of inequality. The aggregate benefit to education thus depends on a country's position in the education distribution. On the other hand, we find a slight transitional increase in education inequality to be beneficial at a very low average level of schooling, but detrimental for growth at a relatively high average level. Allowing for the macroeconomic return to education to be heterogeneous with respect to the degree of inequality is therefore paramount in understanding the relationship between education and development.

Keywords: education, economic growth, distribution of education.

JEL-Codes: D31, I00, O15.

*Institute for Macroeconomics, Vienna University of Economics and Business, Austria. petra.sauer@wu.ac.at.

†Università del Piemonte Orientale, Italy and Vienna University of Economics and Business, Austria. martin.zagler@wu.ac.at.

1 Introduction

The broad concept of human capital comprises aspects inherent in people, which are - as in the case of genetic abilities, skills and talent - either given or - as in the case of education, experience and health - develop over time. In this context education obtained through the formal schooling system takes on an essential role in linking those two components of human capital. Education is able to compensate for congenital differences as well as educational gaps arising in early childhood. Equal access to education therefore helps to secure equality of opportunities.[1]

The aggregate stock of human capital is considered a key element in the determination of economic development. This is true for industrialized countries, where human capital is vital for technology-driven sustainable development and for developing countries, where education is an essential factor for hauling societies out of poverty. Therefore, neoclassical and endogenous growth theories have attributed a special role to the stock of human capital in bringing about technological progress through positive education externalities (Lucas, 1988), idea creation as a basis for innovation (Romer, 1990), or imitation and adoption (Nelson & Phelps, 1966 and Aghion & Howitt, 1996). These theories suggest a direct link from the level of human capital to either the level of output (for the case of neoclassical growth theories), or the change in output (in endogenous growth theories).

The link between education and the aggregate stock of human capital is not straightforward. It depends on schooling quality and spillovers, related to the distribution of human capital within an economy. If the individual returns to education are identical across people and diminishing on the margin (Galor & Moav, 2004), then increasing the education of the less educated would enhance the stock and the average productivity of human capital. But people may differ both in their inherent abilities, skills and talents, as well as their capability to develop them over time. Even if people differ, more equality may lead to an improvement in the return to human capital if the actual distribution is more unequal than the optimal distribution, in which marginal returns are equalized across people. Or, as Fan *et al.* (2001) noted, "if people's abilities are normally distributed, then a skewed distribution of education opportunities represents large welfare losses." The theoretical literature gives ample evidence for this possibility (Sauer & Zagler, 2012). In particular, López *et al.* (1998) highlight the imperfect tradability of education, causing marginal products not to be equalized across individuals and aggregate income to depend not only on the total level but also on the distribution of the respective asset. It is due to these peculiarities that, in the presence of credit market constraints and human capital indivisibility, social inheritance of education and/or education externalities, the degree of human capital inequality negatively affects not only the average stock but also the macro return to human capital.

[1] As from now we abstract from other components of human capital and use the notions of human capital and education interchangeably. Moreover, when talking about education we are always considering education obtained through the formal schooling system. Even if this seems a substantial abstraction, it is not only necessary due to data limitations but also reasonable, as formal education is the component of human capital which can be affected most easily by policy.

Starting with the influential contribution of Mankiw *et al.* (1992), numerous works have aimed at finding empirical support for the theoretically predicted strong relation between human capital and economic growth. Mankiw *et al.* (1992) find a significant and positive relationship between economic growth and human capital accumulation (measured by school enrollment). Due to its perceived importance, the same human capital variable was used as one of three fixed variables in Sala-i-Martin (1997a, 1997b). Nonetheless, the author himself reports that human capital had a significant positive effect on economic growth in only 47% of the four million regressions estimated. In a follow-up study, using Baysian averaging, Doppelhofer *et al.* (2004) demonstrate a positive impact of education in 80% of their cases.

The increasing availability of sound data on aggregate educational attainment[2] has enabled many researchers to confirm empirically the expected positive relation between the average stock of human capital and income growth. The macroeconomic return to education seems, however, to depend on institutions (e.g. Pritchett, 2001) and the quality of education systems (e.g. Hanushek & Kim, 1995). In developing economies in particular, the performance of the education system often depends on the availability of qualified teachers. Human capital formation may thus differ according to the target group. In this respect, Hanushek & Woessmann (2012) demonstrate that schooling has a positive but distinct impact on economic growth, depending on whether it is targeted at basic literates or high performers.

The distribution of human capital may affect the efficiency of human capital formation, and it may also lead to a positive (technological) education externality. In our work, we thus aim to demonstrate that the aggregate marginal benefit to education varies according to the position in the education distribution. We deviate from the literature outlined above, which postulates a simple effect of education on economic growth, and from the theory that redistribution of human capital by ensuring that the distribution of the current generation of school graduates is more evenly distributed than for the retiring generation has only a direct effect on economic performance (e.g. Castelló-Climent, 2010a and Castelló-Climent, 2010b). We thus presume the dominance of an indirect relation, working through the macroeconomic return to education.

We use Barro and Lee's (2013) education data set and compute Gini coefficients of educational attainment for a panel of 134 countries ranging over the period from 1950 to 2005 at five-year intervals. We follow a conventional convergence specification based on the augmented Solow model. This specification is derived from the theoretical exogenous growth model and states that the rate of growth of an economy depends on the distance from the steady state. Mankiw *et al.* (1992) identify the steady state with investment rates, population growth, and average human capital. We add a distributional measure for human capital to this conditional convergence specification. Moreover, we argue that the specification of the relationship between average educational attainment and economic

[2]See Cohen & Soto (2007), Barro & Lee (2013), Lutz *et al.* (2008).

development should allow for a macroeconomic return to education that varies with changes in educational inequality. By applying the system GMM estimator to linear benchmark equations and an interactive specification, we find evidence supporting the presumed heterogeneous and indirect relationship. Robustness of this result is established by introducing a threshold model which tests for education inequality regimes. As this approach has not been applied in empirical studies so far, it provides new insight into the mechanics and channels of the link between education, its distribution and economic development. Moreover, it adds to the extensive empirical literature that deals with computing reliable estimates of the macroeconomic return to education.

The remainder of this paper is organized as follows. Section 2 provides a survey of the theoretical literature on the relevance of the human capital distribution for schooling quality, institutions and externalities, thus for economic development. Section 3 summarizes existing empirical evidence. We describe our data and the methodology in sections 4 and 5. Estimation results are summarized in section 6. The threshold-estimation model is presented in section 7. Finally, we conclude in section 8.

2 The Role of Human Capital Inequality in Economic Development

Economists have long analyzed the relationship between inequality, in particular inequality in income and economic growth. Whereas early approaches underlined the beneficial nature of inequality for economic development, the modern perspective (Galor, 2009) stresses the potential of inequality to curb economic growth.[3] In this line of research, besides the distribution of wealth and income, the distribution of human capital is considered to be an important aspect of the overall degree of inequality within a society. In this regard, Rehme (2007) presents a model where public education financed through proportional income taxation affects the distribution of education, which is in turn the main determinant of the distribution of income.

Some important models of economic development and the distribution of educational attainment focus on the human capital accumulation channel and highlight the effect of inequality on education investment decisions and hence on changes in the economy's income level. Thereby, they are able to explain persistent differences in educational attainment and income within as well as across countries. If credit markets are imperfect or fully absent, initial wealth is the only source for financing human capital accumulation and the poor are constrained in their education investment. Inequality in the initial distribution of wealth therefore adversely affects the division of the population between skilled and unskilled labor. This, in turn, may hinder a society from achieving its full economic potential, both in the short run and in the long run (e.g. Galor & Zeira, 1993).

Initial differences in individuals' socio-economic background also directly translate into heterogeneous education investment decisions. Based on strong empirical evidence on the influence of students'

[3]For good surveys on the literature about the relationship between inequality and growth see García-Penalosa (1994), Aghion *et al.* (1999) and more recently Galor (2009).

socio-economic background in determining educational outcomes, Mejía & St.Pierre (2008) argue that there are crucial complementary factors in the process of human capital formation that are non-purchasable in the market.[4] Well endowed agents accumulate human capital and provide skilled labor, whereas the badly equipped choose to supply unskilled labor. Hence, the aggregate outcome again depends on the share of families with low socio-economic status. Moreover, if individual human capital is subject to decreasing returns to investment, inequality in the distribution of education impairs the level as well as the average productivity of human capital, thus the level of and growth in income. This negative relation persists and compounds in the long run through the intergenerational transmission of education within families as well as amplifying relations between education and fertility choices (e.g. Moav, 2005; de la Croix & Doepke, 2003) and/or life expectancy (e.g. Castelló-Climent & Doménech, 2008).

The models presented by now are based on the assumptions that education is solely funded privately and that education quality is homogeneous. The political economy approach to the macroeconomic effects of human capital inequality accounts for the possibility that publicly provided education is able to mitigate the adverse effect of education inequality to some extent. But it introduces another dimension of heterogeneity as initial diversity leads to different education regimes, associated with a differing efficacy of education in the formation of human capital. In this context, the effect of education inequality on economic outcomes is twofold. On the one hand, the more equal the distribution of education, the higher the average level of human capital, thus the higher the quality of public schooling. The education distribution is, on the other hand, the basis of a majority voting outcome. The size of the aggregate marginal benefit to education then depends on the productivity of the chosen schooling regime (e.g. Glomm & Ravikumar, 1992) or the relative quality of private and public schooling if both regimes coexist (e.g. Ferreira, 2001). In general, the more equal the distribution of human capital, the higher the quality of public education and the more beneficial is high-productive private schooling for a majority of the population. Therefore, consistent with evidence on the quality of education, if inequality in education is pronounced, schooling quality will be low, so that an extra year of education will not produce much additional human capital.[5]

Furthermore, the distribution of human capital also affects the extent to which spillover effects within broadly educated communities generate positive (technological) externalities. According to Galor and Tsiddon (1997), only when human capital has a high average level and is fairly equally

[4]Such factors that complement time and effort in the formation of human capital are family background variables such as parental education, culture, provision of social connections, installation of preferences and aspiration in children as well as other factors, e.g. neighborhood and peer effects, distance to schools, and different qualities of books, teachers and schools, among other things (Mejía & St.Pierre, 2008).

[5]A similar result can be obtained by introducing education costs (e.g. García-Penalosa, 1993). If it is assumed that education is a human capital intensive activity, education cost will vary according to the proportion of skilled labor in the total labor force. On the one hand, in rich and highly educated countries where education is relatively cheap, inequality reduces the proportion of people who can afford to study and hence impairs growth. On the other hand, in poor and unequal countries with low levels of average human capital education costs are relatively high. A temporary increase in the degree of educational inequality allows for a strong decline in education costs which enables more people to become educated and accelerates growth for some periods.

distributed will a positive externality bring about interactions that increase everybody's productivity. In contrast if the level of human capital is very low, increasing the high quality education at the top of the distribution is able to assist in building up an infrastructure that is supportive of technological progress based on innovation, imitation and entrepreneurship.

These theoretical approaches have clear empirical implications. In general they predict a negative relation between human capital inequality and income growth. Models summarized in the first part of this section imply that the more unequal the distribution of education, the lower the average stock of human capital, thus the lower income growth. If it is additionally assumed that individual returns to education are not homogeneous but are decreasing, the degree of human capital inequality also adversely affects the average return to education. The models surveyed in the second part provide insight into the possible channels of this relation. Therein, human capital inequality acts as a proxy for unobservables such as schooling quality, spillover effects and externalities, which drive the average level of human capital as well as income growth. Both strands of the theoretical literature imply that human capital inequality is indirectly related to income growth through its effect on the average return to education.

Overall, we expect the macroeconomic return to average education to be small if human capital is relatively unequally distributed. The more equal the distribution of human capital, the greater are spillover effects and technological externalities, thus the higher the aggregate marginal benefit to education. Also, if the level of human capital is very low, a positive but temporary relation between education inequality and income growth might be seen if an increase in the degree of inequality helps to raise school quality by increasing the stock of qualified teachers. This clearly suggests that the separate inclusion of human capital and its distribution does not fully capture the heterogeneous nature of this relationship. Also, Rehme (2007) suggests that "conventional growth regressions with human capital and inequality as regressors may miss the richness of the underlying nonlinearities."[6] We therefore propose the introduction of an interaction term between human capital and its distribution to test the above theories.

3 Related Empirical Literature

Empirical research on the relationship between the distribution of education and economic performance follows two directions. One line of research considers the distribution of education as an omitted variable in conventional growth regressions, whose inclusion should deliver more reliable estimates of the macro return to education. López *et al.* (1998) use average schooling as well as the standard deviation of educational attainment as explanatory variables in a GDP per capita regression. By applying fixed effects estimation to a panel of 12 Asian and Latin American countries covering the period from 1970 to 1994, they find a higher degree of inequality in the distribution of education

[6]As the income inequality in Rehme (2007) depends on the inequality in education, our empirical estimation may provide further evidence for this claim, already tested in Rehme (2003).

to be significantly negatively related to GDP per capita. Controlling for distributional aspects as well as for non-linearities reveals the macro return to average schooling to be most pronounced and significant. Fan *et al.* (2001) include the education Gini index in growth regressions. By using fixed as well as random effects estimation in a panel of 85 countries ranging from 1960 to 1990, they find a significantly negative relation between the degree of inequality in the distribution of educational attainment and per capita PPP GDP increments. In a separate regression, the effect of average years of schooling on income is significantly positive. However, if both schooling variables are included in one regression equation, the return to average educational attainment remains positive and significant, but the education Gini turns insignificant, indicating average human capital as an important channel linking inequality and growth.

Another line of research aims at revealing the relationship between the general concept of inequality and economic development. Birdsall & Lodoño (1997) hypothesize that the rising degree of inequality in educational attainment in Latin American countries hinders poverty reduction directly as well as indirectly through its effect on growth. For a sample of 43 economies, they find the standard deviation of educational attainment to be negatively associated with long-term growth in the respective region. Castelló & Doménech (2002) compute Gini indices of human capital for 108 countries from 1960 to 2000, based on the Barro and Lee dataset (2000) on educational attainment. In order to deepen insight into the relation between inequality and economic development they use the initial level of their inequality measure in a reduced-form equation with average growth in per capita income from 1960 to 1990, depending on initial income and average accumulation rates of human and physical capital. All their specifications reveal a significantly negative relationship between educational inequality and growth. Furthermore, by using physical capital accumulation as the dependent variable they show that educational inequality is also indirectly related to economic growth through the accumulation of factors. In their subsequent works (Castelló-Climent & Doménech, 2008 and Castelló-Climent, 2010a), the authors provide evidence for demographic channels, i.e. education differentials in fertility and life-expectancy, to be the most relevant mechanisms in linking inequality, human capital accumulation and growth.

In her substantial empirical research on inequality and economic development, Castelló-Climent (2010a, 2010b) succeeds in verifying the strong negative relation between human capital inequality and income growth, observed in previous cross-section regressions, by estimating a dynamic panel data model that allows for fixed effects as well as persistent and endogenous regressors. Furthermore, the author's findings suggest that the effect of human capital inequality differs across countries according to the level of development. While the relationship between the education Gini coefficient and the per capita income growth rate is significantly negative in low- and middle-income countries, it loses significance in higher-income countries. According to Castelló-Climent (2010b), this result can be traced back to the fact that the major channels through which inequality is predicted to negatively affect income growth (i.e. political instability, credit market imperfection, education differentials in fertility and life-expectancy) are predominantly at work in developing countries.

This paper contributes to the empirical literature on education and growth by combing the two directions and adding a third element. First, we continue along the lines of López *et al.* (1998) in computing reliable estimates of the macro economic return to education that account for the relevance of its distribution among the population. Second, we follow Castelló-Climent (2010a and 2010b) in assessing the overall effect of inequality in the distribution of human capital while controlling for unobservable individual effects, dynamic panel bias as well as endogenous and persistent explanatory variables. As opposed to the estimated direct negative relation between human capital inequality and income growth, we presume the predominance of an indirect relation, which works through the macro return to education. Thus, most importantly, we test whether the aggregate marginal benefit to education varies with the position in the distribution of education. A straightforward approach for dealing with heterogeneous coefficients is the inclusion of an interaction term between the distribution and the average level of human capital.

4 The Data

We construct a panel dataset that contains information about real GDP per capita and variables typically constituting its determinants in a neoclassical growth model, and include the average level as well as the distribution of educational attainment. Data on real GDP per capita, capital stocks and population growth are from the most recent release of Penn World Tables (PWT). PWT 8.0 provides annual time series for 167 countries, overall ranging from 1950 to 2010. As it allows for comparing the productive capacity over countries and over time, we use the output-side measure[7] of real GDP at chained PPPs (base=2005). Moreover, we compute the growth rate of capital stocks per capita using a deflated measure of capital stock at current PPPs.

In order to estimate the degree of inequality in the distribution of human capital we apply the Gini coefficient as a relative measure of dispersion to the distribution of educational attainment within a concerned population, following the pioneering work by López *et al.* (1998) and Fan *et al.* (2001) and 2002).[8] The concept of the education Gini coefficient is similar to that of the widely used income Gini, which is defined "...as the ratio to the mean of half of the average over all pairs of the absolute deviations between (all possible pairs of) people." (Deaton 1997 in Fan et al. 2001, 7). However, data on the exact number of years of schooling are unavailable at the macro level, hence years of education are inferred from the usual duration of formal schooling that is required for the highest degree obtained. Formal education is, hence, a categorical rather than a continuous variable. It has

[7]While traditional measures have been based on prices of domestic absorption, the new output-side measure in PWT 8.0 additionally accounts for differences in export and import prices (see Feenstra *et al.*, 2013). This measure permits comparisons both across time and between countries, so that it is an ideal measure of GDP for our purposes.

[8]The method has been widely applied, e.g. by Castelló & Doménech (2002), Checchi (2000), Castelló-Climent (2010a and 2010b) and Castelló & Doménech (2002 and 2008).

a lower boundary at zero years of schooling, accruing to people without any formal education, an upper boundary, given by the cumulative duration of tertiary education and jumps corresponding to transitions from one education level to another. For each country and time interval the education Gini coefficient is, thus, given by,

$$G^E = \frac{N}{N-1} \frac{1}{\mu} \sum_{i=1}^{6} \sum_{j=i}^{5} |\tilde{s}_i - \tilde{s}_j| \, a_i a_j \tag{1}$$

where $\tilde{s}_i$ and $\tilde{s}_j$ depict the cumulative years of formal schooling required to complete the respective education level, indexed by i or j. a_i and a_j are the shares of the population for which level i/j is the highest attained. μ are average years of schooling. Finally, the term $\frac{N}{N-1}$ adjusts the Gini coefficient for small population size. We take all necessary information from the most recent release of the Barro and Lee (2013) schooling dataset.[9] Accordingly, we consider seven categories of educational attainment[10]: no schooling, incomplete and complete primary schooling, the first and second cycle of secondary schooling, incomplete and complete higher education. The population shares and average years of schooling refer to the population aged 15 years and over. The country and level specific duration of formal schooling is derived from Barro and Lee (2013)[11] figures of average years of schooling at each level and the corresponding attainment data. The education Gini is thus the total difference in years of schooling, weighted by population shares and standardized by the average years of schooling in the population. According to (1) the education Gini lies in a range between 0 and 1, indicating perfect equality and perfect inequality, respectively.

Through the combination of both data sources we derive an unbalanced panel[12] consisting of 134 countries from 1950 to 2010 at five-year intervals. We estimate the model (see section 6) both including and excluding the years affected by the 2007 financial crisis.[13] We find that the fit of the model that includes the financial crisis is slightly worse. This makes sense as the financial crisis has hit developed economies much more strongly than developing economies. In order to avoid unwanted distortions we have preferred to truncate our sample in 2005[14] and end up with 1313 GDP- and 1608 schooling-observations.[15]

Across the whole panel, the mean of average years of schooling and the education Gini coefficient

[9]Their methodological improvements (they exploit information from consistent census data, improved their estimation technique for filling in missing observations and use new calculations of mortality rates by age and education as well as estimates of completion ratios by age) address the concerns raised by Cohen & Soto (2007) and de la Fuente & Doménech (2006) and should have significantly increased the quality of their educational attainment data. Barro & Lee (2013) also extended the time and individual dimension and report attainment figures ranging from 1950 to 2010 in five-year intervals for the population aged 15 and over, disaggregated by sex and age.

[10]The classification scheme follows UNESCO's International Standard Classification of Education (ISCED).

[11]Barro & Lee (2013) use data on the typical duration of primary and the two levels of secondary education for each country from issues of the UNESCO Statistical Yearbook. For higher education a duration of four years is assumed for all countries and for all years.

[12]The data are available from the authors upon request. Appendix A provides a list of countries included in our panel dataset by region and reports when various parts of the world enter the dataset.

[13]The data for 2005 to 2010 have only been made available after the submission of the first draft.

[14]The results including observations up to 2010 are available from the authors upon request.

[15]We have also run our estimation excluding OPEC member countries. The estimated effects of schooling and the distribution of human capital on economic performance differ only marginally. These results are available upon request from the authors, too.

is 5.62 and 0.46, respectively (see Table 1). The minimum and maximum values of the concerning schooling variables indicate the existence of huge differences, not only between regions and countries, but also over time. From Figure 1 it becomes evident that an overall trend of education expansion, accompanied by a reduction of inequality in the distribution of education has taken place over the period under study. While the distribution of average years of schooling across the sample has been skewed to relatively low values in 1950, it is skewed towards educational achievement above ten years in 2005. The distribution is, however, quite spread out and shows a second mode below five years of schooling, indicating that huge differences across countries still persist. In contrast, the distribution of the education Gini coefficient has narrowed and is concentrated at a relatively low value in 2005. Countries have thus been converging in terms of their educational distribution.

Table 1 here.

Figure 1 here.

In 2005, across all 134 countries in the sample educational attainment averages were at 7.84 years of schooling, with the respective value for the education Gini being 0.33 (see Table 1). Average years of schooling range from 1.24 years in Mozambique to 12.91 in the United States. Education is most evenly distributed ($G^E = 0.05$) in the Czech Republic. By contrast, Niger reports the maximum education Gini of 0.82, relating to 77 % of the population without any formal education. Indeed, high shares of non-formally educated people coincide with high education Gini values. In all countries with education Ginis greater than 0.5, at least half of the population did not attain any formal education. South Asian and Sub-Saharan African countries are located at the upper left in the level-distribution plane of Figure 2. They thus report, on average, the lowest level of schooling and the highest degree of educational inequality in 2005. In contrast, Advanced Economies as well as European and Central Asian countries, exhibiting high average educational attainment in conjunction with a low degree of inequality, are located at the bottom right. The general shape of the relation between the average level of and the degree of inequality in educational attainment within the remaining regions, reporting medium values of years of schooling and the education Gini coefficient in 2005, is mainly driven by highly-dynamic countries. The development of, for example, Iran in the Middle East, the Republic of Korea in East Asia or Brazil in Latin America, was characterized by enormous educational expansion and a a swift decline in educational inequality (see Figure 3). These countries thus feature values of the two variables on schooling that span almost the whole plane.

Figure 2 here.

Even though the overall panel relation between years of schooling and the education Gini coefficient remains negative, the slope varies with the location in the level-distribution plane. While it is negative and steep above an education Gini of 0.5, it becomes successively flatter as the degree of inequality decreases and the average level of educational attainment increases. It therefore matters at which level of educational attainment one observes the relation between inequality and growth and, vice versa, at which degree of inequality one observes the effect of years of schooling on income growth. Most importantly, however, the within variation differs across countries, even if their educational conditions have been similar at the beginning of the sample period (see e.g. Niger and Iran in Figure 3). In addition, the relation between average years of schooling and the education Gini coefficient within countries over time does not need to be strictly negative. Clearly, in Figure (3), educational inequality remained constant until 1990 in the Czech Republic. Thereafter, the distribution of educational attainment gradually became more equal, as it did in the United States. In contrast, the degree of educational inequality did not change significantly in the United Kingdom, while it increased in France until 1985. Similar levels of average educational attainment therefore involve different compositions of the educational structure, reflected in varying degrees of inequality. The analysis of the direct and indirect growth effects of such variations in the educational Gini coefficient is, thus, what is of prime interest for our work.

Figure 3 here.

5 Estimation Method

We investigate the relationship between income growth and the average level simultaneously with the distribution of educational attainment by adopting an augmented version of a convergence specification. This specification is derived from the closed form solution of the theoretical Solow model. In this exogenous growth model, the rate of growth outside its long-run steady state depends on the current level of output and its steady-state level. The steady state of output in turn depends on several exogenous variables, such as the economy's net investment rate in physical capital and population growth. In an influential seminal paper, Mankiw *et al.* (1992) added the level of human capital[16] as an additional steady-state determinant. The previous theoretical considerations give strong indication that the steady state does not only depend on the level, but also on the distribution of human capital. Specifically, theory implies that the education distribution affects the aggregate marginal benefit to education as it has an impact on schooling quality and externalities. Our main econometric specification is thus given by the following equations.

$$\Delta y_{i,t} = \gamma_1 \ln(y_{i,t-\tau}) + \gamma_2 \Delta k_{i,t} + \gamma_3 \Delta n_{i,t} + \beta_1 \ln(S_{i,t}) + \beta_2 G^E_{i,t} + \delta I_{i,t} + \epsilon_{i,t} \tag{2}$$

$$\epsilon_{i,t} = \xi_t + \eta_i + \nu_{i,t} \tag{3}$$

The dependent variable, $\Delta y_{i,t} = \ln(y_{i,t}) - \ln(y_{i,t-\tau})$, is the growth rate of real GDP per capita in country i over the time interval τ, i.e. 5 years. $y_{i,t-\tau}$ is the corresponding level of real GDP per capita of the preceding period $t-\tau$, γ_1; it thus captures the rate of convergence. Estimating equation (2) is

[16] In their main estimations of a static as well as dynamic augmented Solow model, Mankiw *et al.* (1992) use school enrollment rates in order to proxy for human capital accumulation. The authors demonstrate, however, that their model can alternatively be expressed in the level of human capital, resulting in different coefficients on saving and population growth.

actually equivalent to estimating an equation in the level of GDP per capita and controlling for the lagged dependent variable. The coefficient γ_1 would then, however, have a positive sign. We prefer this specification for two reasons. In this version, we can directly test whether human capital has a level effect on output, or whether it alters the rate of economic growth. If we cannot reject $\gamma_1 \neq 0$, the impact of a change in human capital would be on the rate of growth, thus implying an endogenous growth model (Lucas, 1988). Otherwise, the specification is identical to an exogenous growth model predicting convergence conditional on the steady-state determinants. Thus, the null hypothesis for γ_1 is a direct test whether economic growth is endogenous or not. Furthermore, should economic growth be endogenous, it can no longer be theoretically ensured that GDP is stationary in first differences, whereas the growth rate would remain stationary in first differences along a balanced growth path.

We further include $\Delta n_{i,t} = ln(n_{i,t}) - ln(n_{i,t-\tau})$, the population growth rate[17], and $\Delta k_{i,t} = ln(k_{i,t}) - ln(k_{i,t-\tau})$, the growth rate of capital stock per capita, as control variables. The composite error $\epsilon_{i,t}$ consists of vector of time dummies ξ_t, a time invariant country specific effect μ_i and a remaining idiosyncratic error $\nu_{i,t}$ of country i in period t.

The three explanatory variables of prime interest are the level of human capital, measured as the logarithm of average years of schooling $\ln(S_{i,t})$, its distribution, measured by the education Gini coefficient $G^E_{i,t}$, and an interaction term $I_{i,t}$,

$$I_{i,t} = \ln(S_{i,t}) * G^E_{i,t} \tag{4}$$

which is a non-linear function of $S_{i,t}$ and $G^E_{i,t}$ and captures their combined growth effect. In case we cannot reject $\delta = 0$, (2) represents a simple additive specification where the coefficient on average years of schooling β_1 estimates the elasticity of the growth rate of real GDP per capita with respect to $S_{i,t}$ across all levels of $G^E_{i,t}$. Vice versa, β_2 estimates the change in GDP growth associated with a one-unit change in $G^E_{i,t}$ across all levels of $\ln(S_{i,t})$. Otherwise, the coefficient β_1 in (2) estimates the percentage change in GDP growth associated with a one-percentage change in $S_{i,t}$ when $G^E_{i,t}$ is equal to zero, with the reverse being true for β_2. The coefficient on the interaction term δ measures either the change in β_1 associated with a one-unit change in the distribution of education or the change in β_2 associated with a one-unit change in logged average years of schooling. If δ is statistically significant, the combined effect is relevant and can be deducted from (2) via conditional estimates, i.e. the average effect of $\ln(S_{i,t})$ and $G^E_{i,t}$ on GDP growth, conditional on particular levels of $\ln(S_{i,t})$ and $G^E_{i,t}$, respectively.

Our general specification (2) nests several theoretical and empirical strands of literature, and we will estimate those separately. First, the Mankiw *et al.* (1992) model can be retrieved from (2) by setting $\beta_2 = \delta = 0$. Second, we can reproduce the estimation by Fan *et al.* (2001) by setting either

[17]Here, we deviate marginally from Mankiw *et al.* (1992) by using the population growth rate instead of warranted growth, $ln(\Delta n_{i,t} + a + d)$, where a is the exogenous growth rate of technical progress and d the rate of depreciation. Given a and d are constant, Mankiw *et al.* (1992) impose a nonlinearity in the estimator. In line with most of the subsequent literature, we prefer a linear(ized) version of the estimator.

$\beta_1 = \delta = 0$ or $\beta_2 = \delta = 0$ or just $\delta = 0$. The latter case also resembles the estimation equation employed by Castelló-Climent (2010a). However, the considerations in section 2 have given strong indication for heterogeneity in the coefficients on the schooling variables. We have argued that the impact of human capital is not uniform across educational systems that differ in their degree of educational inequality. This makes the inclusion of the interaction term a first empirical test to this literature. Theory also suggests that poor economies may transitionally benefit from an increase in education inequality. Furthermore, the aggregate productivity of education and spillover effects, i.e. the macroeconomic return to education, are predicted to be higher in more equal societies.

Note that we also have to distinguish between a mechanical and a behavioral relationship. High and low average educational attainment is associated with low and high values of the education Gini coefficient by construction. In between these extremes, however, we find within-country developments to be heterogeneous. On the one hand, we have to control for the negative relationship. On the other hand, the average level and the distribution of educational attainment are not collinear, so their effects on growth can be separately identified (see discussion about Figure 3 in section 4).

In any specification of equation (2) we are estimating a dynamic model in real GDP per capita, which allows for country-specific characteristics. Therefore, an appropriate estimation technique should be able not only to deal with unobservable individual effects, but also with the dynamic panel bias. That is, the lagged dependent variable is not only necessarily correlated with the country-specific intercept, but also not strictly exogenous with respect to the time-varying error, i.e. $cov(y_{i,t-\tau}, \nu_{t-\tau}) \neq 0$. Moreover, the issue of endogeneity also arises with respect to the explanatory variables of our interest. For example, it is reasonable to assume the average level and the distribution of human capital to be determined simultaneously with income. By having more means for investing in education in general as well as for providing high quality public education, quickly growing and rich economies might not only accumulate human capital, but would also aim at achieving a more equitable distribution of educational attainment. This issue of reverse causality has already been subject to discussion on theoretical as well as empirical grounds (e.g. Bils & Klenow, 2000).

In order to cope with these estimation problems we use the instrumental variable approach of the system General Method of Moments (GMM),[18] initially proposed by Arellano & Bover (1995) and Blundell & Bond (1998). On the one hand, differencing eliminates unobservable individual effects. The identifying assumption of lagged levels being orthogonal to the first difference of the time-varying error enables to use them as internal instruments for the lagged dependent variable and other endogenous regressors. On the other hand, the identifying assumption of lagged first differences being orthogonal to the time-invariant error component makes them valid instruments in the levels equation. System GMM then estimates a stacked system of equations in first differences and in levels, simultaneously. We assume lagged GDP per capita to be predetermined so that $y_{i,t-2\tau}$ and $\Delta y_{i,t-\tau}$ (and deeper lags)

[18] The sensitivity of the estimates to the method used for estimation is investigated by a comparison to fixed effects and OLS estimates in appendix B.

are available as instruments in the equation in first differences and the levels equation, respectively. By contrast, treating population and capital-stock growth as well as average years of schooling and the education Gini coefficient endogenous necessitates to go one further period back in order to obtain valid instruments.

Consistency of system GMM crucially hinges on identifying assumptions securing the validity of instruments, i.e. exogeneity of lagged levels and lagged differences in the first difference and the levels equation, respectively. The assumption needed for instruments added by the levels equation to be valid is not trivial, since it requires stationarity of the explanatory variables. This is secured, however, by transforming data into deviations from period means by adding time dummies, as in (2)[19]. Evaluating whether the identifying assumptions hold is essential. We therefore report two specification tests. First, the Hanson test of over identifying restrictions tests the null hypothesis of joint validity of the whole instrument set. Moreover, it has to be confirmed that the errors are serially uncorrelated. The second test we perform is the Arellano-Bond test for autocorrelation, which aims to detect first-order serial correlation in levels through testing for second-order serial correlation in the residuals in differences.

The system GMM estimator generates a number of instruments that are quadratic in the time dimension (T). The instrument count can hence easily grow large relative to the sample size as T rises, and may induce severe finite-sample problems. Typical for all instrumental variable techniques, too many instruments can overfit endogenous variables, failing to expunge their endogenous components and biasing coefficient estimates (Roodman, 2007). Moreover, the Hansen test statistic reveals that overall the instruments validity becomes weak as instruments become numerous. In order to secure reliability of estimation results, we limit the instrument set to the first available lag of predetermined and endogenous variables, respectively.

6 Results

We estimate equation (2) in a dynamic panel over 55 years and 134 countries with a system GMM estimator in order to explore the relationship between economic development, average educational attainment and the degree of educational inequality.

Table 2 summarizes our regression results. We present four specifications. The first specification reported in column (1) reproduces a conventional convergence specification, augmented with the level of human capital (Mankiw *et al.*, 1992). The second column replaces the log of schooling with the Gini coefficient of educational attainment. In the third column, we include both the log of schooling to approximate for average human capital and the education Gini in order to measure its distribution. Finally, in the fourth column, we adopt the methodology presented in equation (2) and add an

[19]Yet, Roodman (2006) demonstrates this requirement to hold if initial deviations from a steady state of a series are uncorrelated with the fixed effect, which is likely to be the case if a the starting point of a series lies far behind the analyzed sample period. If so, stationarity would be assured even without time demeaning.

interaction term between average years of schooling and the education Gini.

Table 2 here.

The middle panel of Table 2 reports specification tests peculiar to the system GMM estimator. Limiting the instrument set to the first available lag of predetermined and endogenous variables, respectively, enables us to ensure that the number of instruments falls below the number of observations in each regression. Moreover, the Hansen test statistic reveals that overall instruments are valid in each specification. Finally, p-values of the Arellano-Bond test allow for accepting the H_0 of no second-order serial correlation in first differences.

In all specifications the coefficient on lagged GDP per capita has the expected negative sign and is statistically significant. Hence conditional convergence is confirmed to be relevant for the economies building up our sample.[20] Accordingly, countries with higher income exhibit lower growth rates, with the corresponding elasticity ranging from -0.046 to -0.085. In accordance with theoretical predictions, income and capital-stock growth are positively related at a substantial magnitude. An increase in population growth curbs economic development. However, we can reject the null hypothesis of no effect of population growth at the 5% significance level only in the first specification.

When estimating the marginal benefits to education without allowing for distributional aspects we do not find the positive effect of average schooling to be statistically significant. In contrast, decreasing the degree of educational inequality raises growth rates. That is, a reduction in the education Gini coefficient by 0.1 (one standard deviation, equal to 0.22) increases five-year growth rates by 0.031% (0.068%). With a semi-elasticity of -0.055 (-0.12), the effect of the education Gini is even larger if average schooling is controlled for. However, due to the negative relation between the average level and the distribution of schooling we suspect that the education Gini is absorbing the positive macro return to education to the extent that it is not completely captured in $\ln(S_{i,t})$. Additional supportive evidence for this presumtion is provided by the specification in column (4). Therein, we introduce the proposed interaction term, thereby testing for heterogeneity in the effect of average schooling with respect to the existing degree of inequality in the distribution of education and, at the same time, for the dependence of the effect of the education Gini on the average level of educational attainment. Allowing for this non-linearity turns out to be crucial, as the macroeconomic return to education turns out to be statistically significant. Moreover, we find a strong and negative combined effect of the two schooling variables. Thus, of particular interest are the conditional estimates, which we derive from the interactive specification (2) as follows:

$$\delta_S = \beta_1 + \delta G^E_{i,t} \tag{5}$$

$$\delta_G = \beta_2 + \delta \ln(S_{i,t}) \tag{6}$$

In order to test for the significance of conditional estimates, we compute conditional t-statistics

[20] Recent evidence by Young (2012) indicates that we may underestimate convergence, as economic growth rates in poor countries, in particular in sub-Saharan Africa, may be higher than officially indicated.

based on conditional standard errors which measure the variability of their associated coefficients at particular levels of the respective variable (Friedrich, 1982). In order to get a sense of the significance of these conditional estimates, the following policy experiments can be considered. First, δ_S gives us the immediate effect of a one percent increase in human capital on economic growth, for a given degree of inequality. Second, δ_G gives us the immediate effect on economic growth of switching from a perfectly equal distribution of education to a perfectly unequal one, holding the average years of schooling constant.

Results for the marginal benefit to education conditional on the degree of educational inequality (δ_S) are presented in Figure 4, which includes both conditional estimates as well es the 10% confidence interval. Accordingly, a one percent increase in average schooling boosts five-year growth rates by 0.535% if education is distributed perfectly equally, i.e. $G^E_{i,t} = 0$. However, with each increase of the education Gini coefficient by one standard deviation, equal to 0.22, this positive effect is reduced by 0.09 percentage points. Thus, the effect diminishes substantially from an elasticity of 0.323 at the lower bound, $G^{E,L}_{i,t} = 0.16$, given by the range of the education Gini which covers 90% of the data, to 0.22 at the sample median ($G^E_{i,t} = 0.41$). At the corresponding upper bound, where $G^{E,U}_{i,t} = 0.9$, the marginal benefit to education is negligible and statistically insignificant. Overall, when the education Gini is above 0.6, we can no longer reject the null hypothesis of no influence of human capital on economic growth at the 10% significance level. This result demonstrates that, in general, average educational attainment is relevant for economic development. However, education matters only if it is not distributed unequally. Above an education Gini of 0.6 - or, for 29% of the data - an increase in education does not have any impact on growth, as schooling quality is low and education then only benefits a small elite. In contrast, the impact of education is stronger, the more equally education is distributed in an economy.

Figure 4 here.

Figure 5 gives the conditional estimates of increasing educational inequality for given levels of schooling. We find that for very low levels of education, the education Gini is positively related to economic growth. At the lower bound, $S^L_{i,t} = 0.8$, given by the range of average schooling covered by 90% of the data, a one standard deviation deterioration of the Gini coefficient would increase five-year growth rates by 0.138%. These positive estimates are statistically significant at the 10% level only for average schooling below 0.7 years (4.3% of the sample). In contrast, above 10 years of schooling, education inequality is significantly detrimental to income growth. At the corresponding upper bound, where $S^U_{i,t} = 10.68$, an increase in the education Gini by one standard deviation reduces growth rates by 0.095%.[21]

[21] Our result contrasts previous evidence from Castelló-Climent (2010a, 2010b), who finds income growth to be negatively related to educational inequality in low- and middle-income countries, but insignificant in high income countries. A possible reason for this disparity is that allowing the effect of inequality to depend on the level of educational attainment enables to account for differences between countries, even within defined income groups. However, although a positive relation is supported theoretically, it might be either driven by outliers or by the omission of the demographic dimension of inequality. That is, fast educational expansion is associated with a swift increase in educational attainment

Figure 5 here.

The coefficients presented in Table 2 only give us the short-run impact of changes in the education system on economic growth. Given the dynamic linkages, these effects will be propagated into the future, as an increase in the rate of growth in period one will lead to a higher GDP in period 2, which in turns generates more growth in period two and so forth. With $0 < \gamma_1 < 1$, this propagation effect will eventually taper off. We can calculate the overall long-run effect of a change in the independent variables by dividing the coefficients estimated in equation (5) by $-\gamma_1$. The conditional short-run estimate for the effect of a one percent increase in human capital at the first quartile of the education Gini in 2005 is $\delta_S = 0.39 - 0.41 * 0.207 = 0.305$. In the long run, this effect multiplies to $\frac{\delta_S}{-\gamma_1} = 0.305/0.085 = 3.588$. Thus, increasing human capital by one percent would lead to an increase in GDP by 3.588% in the long run. At the third quartile of the education Gini in 2005, the conditional immediate effect of $\delta_S = 0.39 - 0.41 * 0.425 = 0.216$ results in a long-run effect of 2.538%. In contrast, at the third quartile of years of schooling in 2005 (9.86), an improvement in the education Gini by 0.1 entails a conditional growth effect of 0.04% and increases GDP per capita by 0.474% in the long run.

Putting this together, we can identify four country groups in our data, differing in the combined effect of average education with its distribution[22]. First, in line with theoretical predictions, for $G^E_{i,t} > 0.6$ and $S_{i,t} \leq 0.7$ one can deduce from our results that in countries with very low levels of education, allocating educational resources to students at the top of the education distribution would generate the most growth. Once the educated population passes a certain threshold, they will contribute to a speedup in economic growth. However, among this 29% of the sample, including e.g. Niger from 1950 to 1980 and in Iran in 1950 and 1955, with education Ginis averaging at 0.94, many countries were near the maximum education Gini. These countries then began to move towards a more equal distribution of education, while growth rates were highly erratic around zero. In the second group of countries, where $G^E_{i,t} > 0.6$ and $S_{i,t} > 0.7$, neither schooling effect is statistically significant. Thus, e.g. in Niger from 1985 to 2005 and the Iran from 1960 to 1985, it would be beneficial to attain a more equal distribution of education in order to enter into the third group. With $G^E_{i,t} \leq 0.6$ and $0.7 < S_{i,t} < 10$, the third group includes 63% of the sample where a public base supporting investment into schooling quality as well as positive (technological) education externalities and spillover effects become stronger the more equal the distribution of education. Accordingly, e.g. in Brazil and the Republic of Korea the macro return to education has been increasing throughout the whole sample period. In contrast, increasing average attainment by one percent in the United Kingdom had the same effect of 0.308% in 1950 as in 2005. Finally, if $G^E_{i,t} \leq 0.6$ and $S_{i,t} \geq 10$, as e.g. in the Republic of Korea from 1995 to 2005 and the United States from 1965 to 2005, it is possible to generate a growth-enhancing effect of redistributing education which is additional to the marginal benefit to increasing

of the youth, while attainment of the elderly usually remains constant. The associated unequal distribution between age cohorts, reflected in higher education Gini values, thus imply a positive growth effect. A consistent analysis of educational inequality within and across age groups would, therefore, be an important aspect for further research.

[22]See Figure 3 for the example countries which follow.

average schooling.

7 Education Inequality Regimes and Threshold Estimation

The main implication of the preceding analysis is that the macro return to education varies with the position in the education distribution. In order to provide additional evidence on this relation, we adopt a threshold effects estimation framework (see Shin, 2007 and Hansen, 1999). This method enables us to statistically determine thresholds which divide the sample into regimes. In our case, the threshold variable is the education Gini coefficient. For two regimes, the threshold model is given by

$$\Delta y_{i,t} = \phi_1 \ln(S_{i,t}) * 1(G_{i,t} < \lambda_1) + \phi_2 \ln(S_{i,t-\tau}) * 1(G_{i,t} \geq \lambda_1) + \gamma X_{i,t} + \epsilon_{i,t} \tag{7}$$

where λ_1 is the threshold value. Based upon specification (7), we test whether we are able to recover the marginal benefits to education, ϕ_1 and ϕ_2, to be heterogeneous across inequality regimes.

In order to obtain an estimator of the threshold value, $\hat{\lambda}_1$, we impose a restriction that each regime must contain at least 10% of the observations. In a system GMM context (Shin, 2007), model (7) is then estimated for each value of education Gini coefficients ranging from 0.2 to 0.8 in steps of 0.05 and generalized minimum distance measures (GMDM) are obtained. A consistent estimator of λ_1 is given by the threshold value which minimizes the GMDM. If one assumes that another threshold value, $\lambda_2 < \lambda_1$ or $\lambda_2 > \lambda_1$, exists, $\hat{\lambda}_1$ is taken as given and $\hat{\lambda}_2$ is estimated in a similar manner, based on the remaining range of education Gini coefficients. This basic procedure (and the corresponding threshold model) can easily be extended to a higher amount of regimes, as long as the sample size within each regime does not become too small.

Table 3 here.

Table 3 presents estimates we obtain from splitting our sample into two, three, or four regimes. In column (1) the estimated threshold $\hat{\lambda}_1$ equals an education Gini coefficient of 0.25, but in both regimes the return to education remains insignificant. In column (2) we obtain three regimes based on two thresholds, $\hat{\lambda}_1 = 0.25$ and $\hat{\lambda}_2 = 0.5$. Below an education Gini of 0.5 the marginal benefit to education is positive and lower for the higher inequality regime, above 0.5 it becomes insignificant. Finally, three thresholds ($\hat{\lambda}_1 = 0.25$, $\hat{\lambda}_2 = 0.55$ and $\hat{\lambda}_1 = 0.75$) divide the sample into four regimes. Again, the return to education is highest in the lowest inequality regime and slightly lower in the second regime. It is further slightly negative in the third and insignificant in the fourth regime.

The coefficients on average schooling are jointly significant in the three as well as the four regimes model. Moreover, a likelihood ratio test[23] which enables to select between different threshold specifications allows us to identify four regimes to be best suited in order to model heterogeneity in the macro return to education.

[23] Likelihood ratio tests on the existence of two, three or four regimes are based on the difference between generalized minimum distance measures. That is, we compare the GMDMs of a specification without any threshold (see column (1) in Table 2) and one threshold in order to test for the existence of one or two regimes, respectively. In doing so, we are able to reject the H_0 of no, one, two and three against the alternatives of two, three and four regimes.

Figure 6 here.

In Figure 6, we present the estimated effect of average schooling conditional on education inequality as it results from the three-regimes (solid lines) and the four-regimes (lighter lines) model, respectively. We also show the boundaries of the confidence interval of the interactive specification, 4. The effect of schooling on economic growth is insignificant for the third and fourth regimes in the three-regime and the four-regime threshold regression. This is consistent with the continuous model, where the coefficient becomes insignificant for a Gini beyond 0.6. Below about 0.6, the lower the Gini, the stronger the effect of schooling on economic growth, both in the threshold models and the continuous model. The estimators of the threshold models fall on the lower bound of the continuous case estimation, but are largely within the bounds of the confidence interval. The threshold model thus provides additional evidence for the macro return to education to vary with the position in the education distribution. Instead of jumping from one regime to another this heterogeneity seems, however, to be appropriately modeled continuously, as it is performed by allowing for the interaction term.

8 Summary and Conclusions

Education obtained through the formal schooling cycle plays a fundamental role, not only for income generation at the individual level, but also for equality of opportunities and economic development at the macro level. The link between education and the aggregate stock of human capital is, however, not straightforward. It depends on schooling quality, externalities and spillovers, related to the distribution of human capital within an economy. Theoretical approaches to economic growth that account for distributional aspects generally predict the degree of human capital inequality to negatively affect income growth through the channel of human capital accumulation. But, theory also provides indication, not only for the effect to differ across countries according to the average level of human capital but, most importantly, also for the macroeconomic return to education to vary with the degree of education inequality. Our central hypothesis has therefore been that the aggregate benefit to education depends on a country's distribution of education. A specification of the real relationship between average educational attainment, its distribution and economic development should thus allow for a heterogeneous macroeconomic return to education and a non-linearity in the effect of educational inequality.

Applying a system GMM estimator to a panel of 134 countries over 55 years from 1950 to 2005, we have been able to recover the main results established in the empirical literature on education inequality and economic growth. But we did not find evidence of a direct, negative effect of education inequality, independent of other variables, notably the average level of schooling.

Accounting for heterogeneous coefficients by including an interaction term between the distribution - measured by the education Gini index - and the average level - measured by average years of schooling - of human capital turned out to be crucial in understanding the relevance of educational attainment and inequality for economic development. We demonstrate, first, that the coefficient on average schooling increases and becomes statistically significant as the appropriate functional form is being estimated. Education thus exhibits a positive impact that is, however, substantially declining in the degree of inequality in the education distribution. Accordingly, countries that show greater educational inequality experience lower macroeconomic returns to education than more equal economies, on average. The robustness of this result is established by introducing a threshold model that tests for the presence of education inequality regimes. Second, we find a slight transitional increase in education inequality to be beneficial at a very low, but detrimental for growth at a relatively high, average level of schooling. The effect is, however, statistically insignificant over the broad middle range of schooling.

The conditional relationship between average educational attainment and income growth implies that educational inequality has a negative, but indirect, effect on economic growth through a dampening effect on the macroeconomic return to education. From this it follows, that the existence of constraints to the equalization of marginal individual returns to education inhibits the aggregate productivity of human capital. Moreover, consistent with evidence on schooling quality, high inequality in the distribution of education constitutes a barrier to education expansion. As education becomes more equally distributed, spillover effects of broadly educated communities predominate and determine the scope of positive education externalities.

Table 1: Summary statistics

		Average years of schooling				Education Gini			
region	*obs*	*mean*	*sd*	*min*	*max*	*mean*	*sd*	*min*	*max*
Panel 1950-2005	1313	5.62	3.03	0.13	12.91	0.46	0.22	0.05	0.99
					2005				
Total	134	7.84	2.74	1.24	12.91	0.33	0.17	0.05	0.82
Advanced Economies	24	10.38	1.54	6.47	12.91	0.21	0.06	0.1	0.33
Europe and Central Asia	20	10.33	1.07	8.57	12.75	0.15	0.05	0.05	0.27
Latin America and Caribbean	21	8.04	1.41	3.99	9.71	0.3	0.09	0.12	0.53
East Asia and the Pacific	16	7.93	2.13	4.29	11.53	0.31	0.09	0.17	0.48
South Asia	6	5.62	2.61	3.41	10.8	0.47	0.14	0.2	0.59
Middle East and North Africa	15	7.22	2.27	2.98	11.28	0.4	0.15	0.2	0.73
Sub-Saharan Africa	32	4.91	2.01	1.24	9.13	0.51	0.17	0.21	0.82

Source: Barro & Lee (2013), own calculations. See Appendix A for a list of countries by region.

Table 2: Regression results

	$\Delta y_{i,t}$			
	(1)	(2)	(3)	(4)
$\ln(y_{i,t-\tau})$	-0.046	-0.062	-0.060	-0.085
	(0.020)**	(0.021)***	(0.019)***	(0.023)***
$\Delta k_{i,t}$	0.399	0.395	0.434	0.469
	(0.063)***	(0.060)***	(0.062)***	(0.056)***
$\Delta n_{i,t}$	-0.889	-0.527	-0.172	0.255
	(0.342)**	(0.391)	(0.479)	(0.526)
$\ln(S_{i,t})$	0.043		-0.081	0.390
	(0.036)		(0.066)	(0.170)**
$G_{i,t}$		-0.311	-0.548	0.535
		(0.170)*	(0.253)**	(0.362)
$\ln(S_{i,t}) * G_{i,t}$				-0.410
				(0.165)**
Obs	1,179	1,179	1,179	1,179
N	134	134	134	134
$\bar{T}$	8.80	8.80	8.80	8.80
$Inst$	87.00	87.00	107.00	128.00
$p(J)$	0.03	0.04	0.15	0.23
$p(ar1)$	0.00	0.00	0.00	0.00
$p(ar2)$	0.23	0.18	0.18	0.18

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes: Standard errors in parenthesis. Time dummies are included for each 5-year time interval of the sample period from 1950 to 2005. Instruments are the level and the first difference of GDP per capita lagged one period as well as the level and the first difference of $\Delta k_{i,t}$, $\Delta n_{i,t}$, $\ln(S_{i,t})$ and $G_{i,t}$ lagged two periods in the first difference and the levels equation, respectively. The instrument set is restricted to the first lag available. $\bar{T}$ is the average number of time observations by country. $p(J)$ is the p-value corresponding to the Hansen test for joint validity of instruments. $p(ar2)$ reports the p-value corresponding to the null of no second order serial correlation in first differences.

Table 3: Threshold model

	$\Delta y_{i,t}$		
	(1)	(2)	(3)
$\ln(y_{i,t-\tau})$	-0.051	-0.059	-0.064
	(0.018)***	(0.018)***	(0.021)***
$\Delta k_{i,t}$	0.438	0.432	0.409
	(0.065)***	(0.060)***	(0.055)***
$\Delta n_{i,t}$	-0.686	-0.178	0.329
	(0.358)*	(0.395)	(0.447)
$\ln(S_{i,t})1$	0.064	0.088	0.112
	(0.040)	(0.042)**	(0.045)**
$\ln(S_{i,t})2$	0.041	0.067	0.090
	(0.034)	(0.030)**	(0.035)**
$\ln(S_{i,t})3$		-0.002	-0.056
		(0.033)	(0.029)*
$\ln(S_{i,t})4$			0.037
			(0.058)
Obs	1,179	1,179	1,179
N	134	134	134
$\bar{T}$	8.80	8.80	8.80
$Inst$	107.00	127.00	147.00
$p(J)$	0.13	0.29	0.60
$p(ar1)$	0.00	0.00	0.00
$p(ar2)$	0.22	0.22	0.11

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes: Standard errors in parenthesis. See notes of Table 2.

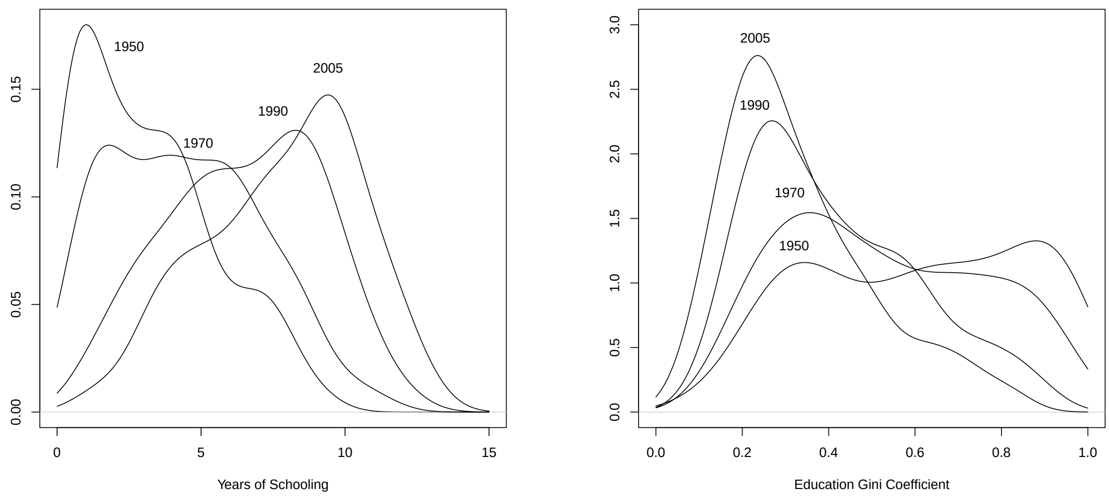

Figure 1: Kernel Density Estimates

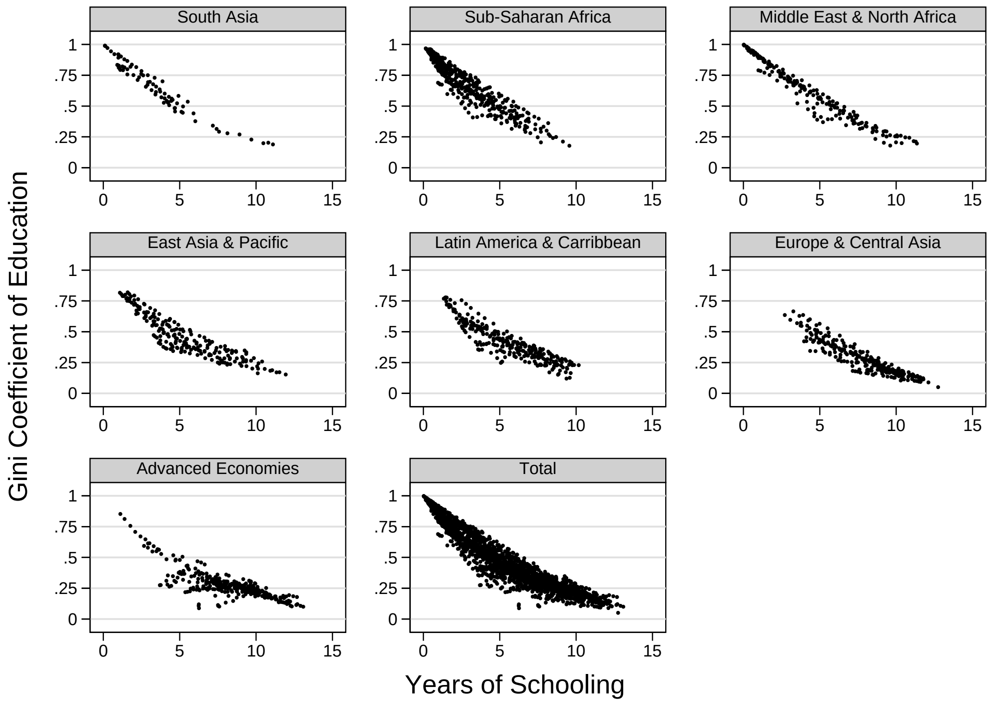

Figure 2: Average Years of Schooling vs. Education Gini Coefficient by Region

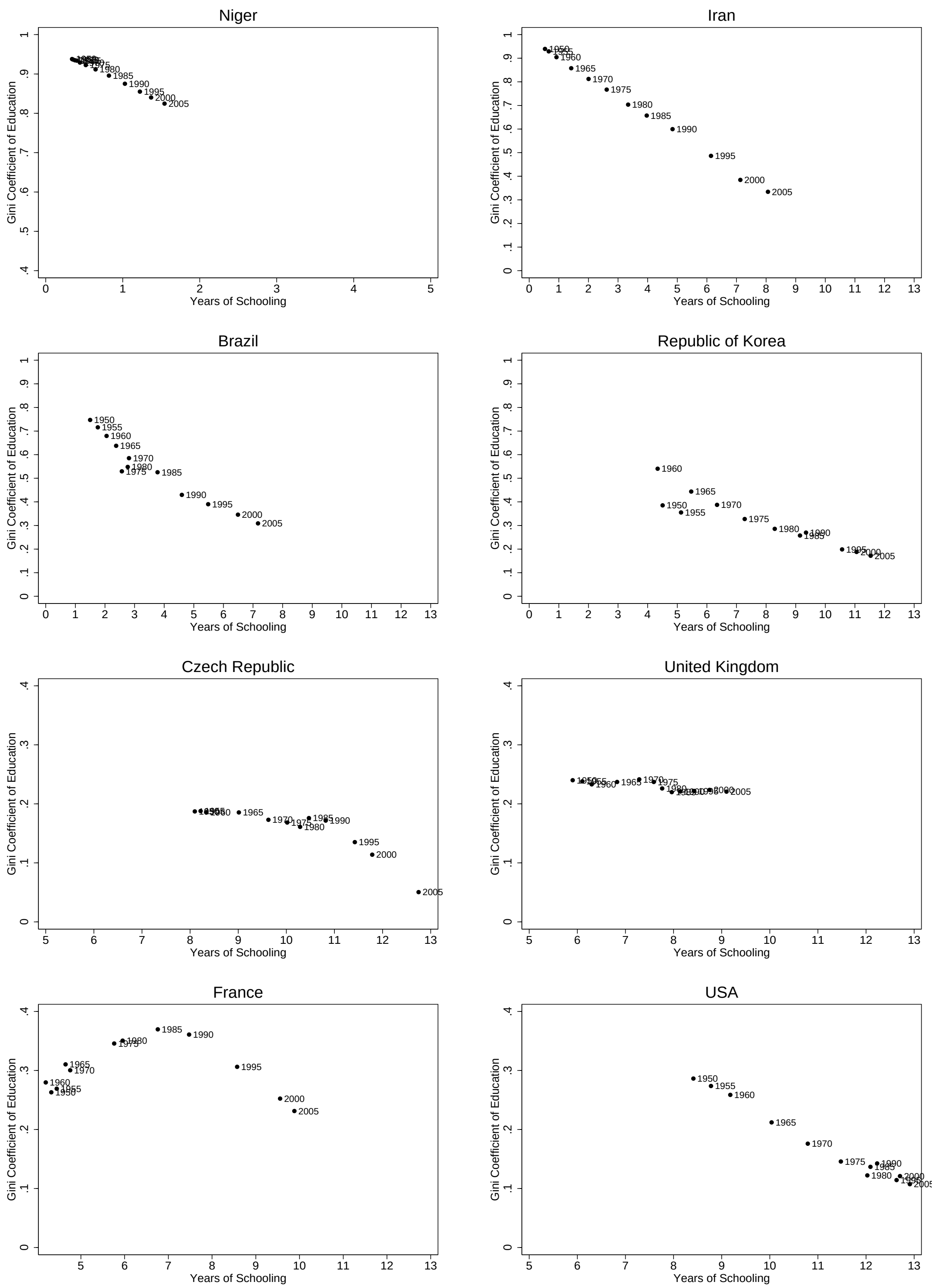

Figure 3: Average Years of Schooling vs. Education Gini Coefficient, selected countries

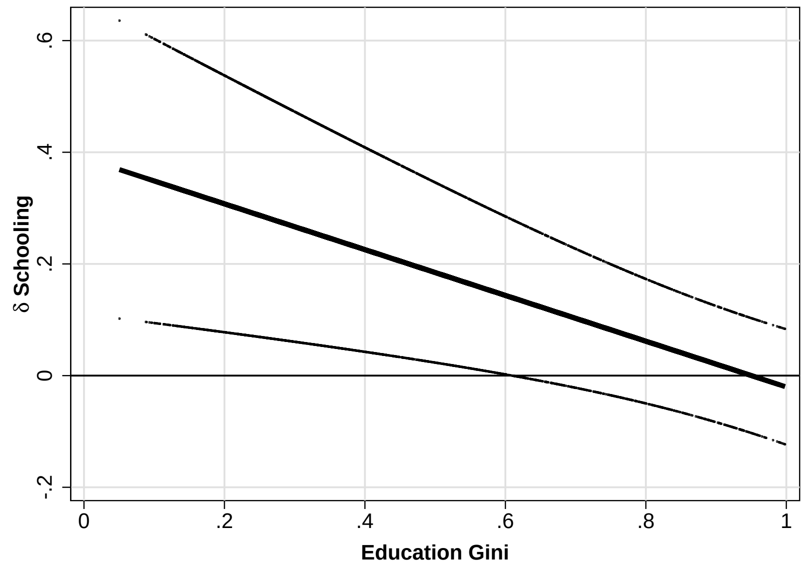

Figure 4: Estimates of the effect of average schooling conditional on the education Gini (δ_S)

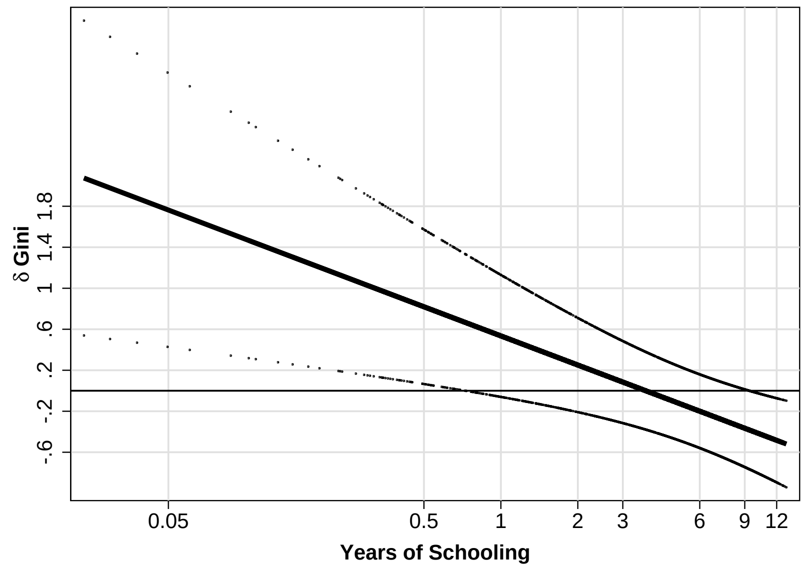

Figure 5: Estimates of the effect of the education Gini conditional on average schooling (δ_G)

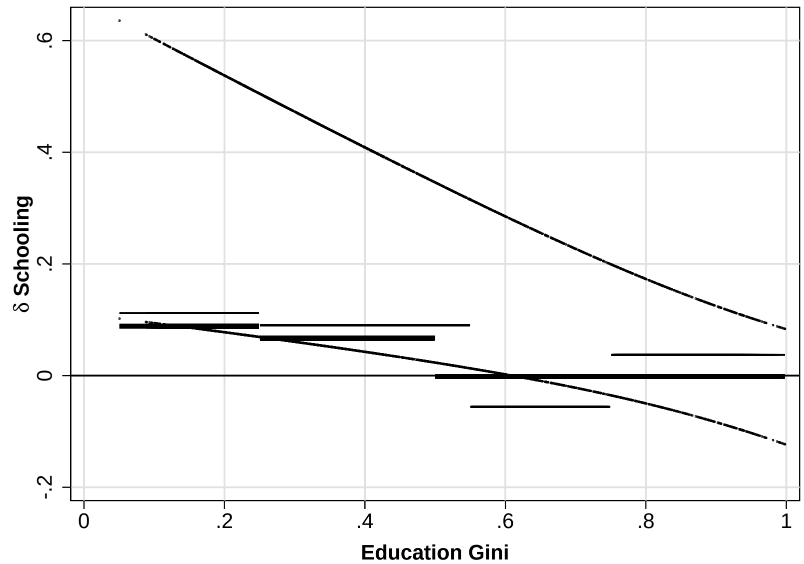

Figure 6: Estimates of the effect of average schooling from the three-regimes (solid lines) and four-regimes (lighter lines) specification

References

Aghion, Philippe, & Howitt, Peter. 1996. Research and Development in the Growth Process. *Journal of Economic Growth*, **1(1)**, 49–73.

Aghion, Philippe, Caloli, Eve, & Garcia-Penalosa, Cecilia. 1999. Inequality and Growth: The Perspective of New Growth Theories. *Journal of Economic Literature*, **4**, 1615–1660.

Arellano, Manuel, & Bover, Olympia. 1995. Another Look at the Instrumental Variable Estimation of Error-Component Models. *Journal of Econometrics*, **68**, 29–52.

Barro, Robert J., & Lee, Jong-Wha. 2000. *International Data on Educational Attainment: Updates and Implications*. NBER Working Paper 7911.

Barro, Robert J., & Lee, Jong-Wha. 2013. A new data set of educational attainment in the world, 1950-2010. *Journal of Development Economics*, **104**, 184–198.

Bils, Mark, & Klenow, Peter J. 2000. Does Schooling Cause Growth? *The American Economic Review*, **90**(5), 1160–1183.

Birdsall, Nancy, & Londoño. 1997. Asset Inequality Matters: An Assessment of the World Bank's Approach to Poverty Reduction. *American Economic Review*, **87**(2), 32–37.

Blundell, Richard, & Bond, Stephen R. 1998. Initial Conditions and Moment Restrictions in Dynamic Panel Pata Models. *Journal of Econometrics*, **87**(1), 115–143.

Castelló, Amparo, & Doménech, Rafael. 2002. Human Capital Inequality and Economic Growth: Some New Evidence. *The Economic Journal*, **1128**, C187–C200.

Castelló-Climent, Amparo. 2010a. Channels Through Which Human Capital Inequality Influences Economic Growth. *Journal of Human Capital*, **4(4)**, 394–450.

Castelló-Climent, Amparo. 2010b. Inequality and Growth in Advanced Economies: An Empirical Investigation. *Journal of Economic Inequality*, **8(3)**, 293–321.

Castelló-Climent, Amparo, & Doménech, Rafael. 2008. Human Capital Inequality, Life Expectancy and Economic Growth. *The Economic Journal*, **118**, 653–677.

Checchi, Daniele. 2000. *Does Educational Achievement Help to Explain Income Inequality?* Working Paper n.11.2000, Universitá degli Studi di Milano.

Cohen, Daniel, & Soto, Marcelo. 2007. Growth and Human Capital: Good Data, Good Results. *Journal of Economic Growth*, **12**, 51–76.

de la Croix, David, & Doepke, Matthias. 2003. Inequality and Growth: Why Differential Fertility Matters. *The American Economic Review*, **93**(4), 1091–1113.

de la Fuente, Angel, & Doménech, Rafael. 2006. *Human Capital in Growth Regressions: How Much Difference Does Data Quality Make?* CEPR Discussion Paper 2466.

Deaton, Angus. 1997. *The Analysis of Household Surveys: A Microeconomic Approach to Development Policy.* John Hopkins University Press, Baltimore and London.

Doppelhofer, Gernot, Miller, Ronald I., & i Martin, Xavier Sala. 2004. Determinants of Long-Term Growth: A Bayesian Averaging of Classical Estimates (BACE) Approach. *American Economic Review*, **94(4)**, 813–835.

Fan, Xibo, Thomas, Vinod, & Wang, Yan. 2001. *Measuring Education Inequality: Gini Coefficients of Education.* World Bank Working Paper 2525.

Fan, Xibo, Thomas, Vinod, & Wang, Yan. 2002. *A New Dataset on Inequality in Education: Gini an Theil Indices of Schooling for 140 Countries, 1960-2000.* Mimeo, The World Bank.

Feenstra, Robert C., Inklaar, Robert, & Timmer, Marcel. 2013. *PWT 8.0 - a user guide.* PWT8.0 Documentation http://www.rug.nl/research/ggdc/data/penn-world-table.

Ferreira, Francisco H.G. 2001. Education for the Masses? The Interaction Between Wealth, Educational and Political Inequalities. *Economics of Transition*, **9**(2), 533–552.

Friedrich, Robert J. 1982. In Defense of Multiplicative Terms in Multiple Regression Equations. *American Journal of Political Science*, **26**(4), 797–833.

Galor, Oded. 2009. Inequality and Economic Development: An Overview. *In:* Galor, Oded (ed), *Inequality and Economic Development: The Modern Perspective.* Elgar Publishing.

Galor, Oded, & Moav, Omer. 2004. From Physical to Human Capital Accumulation: Inequality and the Process of Development. *Review of Economic Studies*, **71**, 1001–1026.

Galor, Oded, & Tsiddon, Daniel. 1997. The Distribution of Human Capital and Economic Growth. *Journal of Economic Growth*, **2**, 93–124.

Galor, Oded, & Zeira, Josph. 1993. Income Distribution and Macroeconomics. *The Review of Economic Studies*, **60**(1), 35–52.

García-Penalosa, Cecilia. 1993. *Inequality and Growth in Economies with Education and Redistributive Taxation.* M. Phil. thesis, Oxford University, UK.

García-Penalosa, Cecilia. 1994. Inequality and Growth: A Note on Recent Theories. *Investigaciones Económicas*, **18**(1), 97–116.

Glomm, Gerhard, & Ravikumar, B. 1992. Public versus Private Investment in Human Capital: Endogenous Growth and Income Inequality. *Journal of Political Economy*, **100**(4), 818–834.

Hansen, Bruce E. 1999. Threshold effects in non-dynamic panels: Estimation, testing, and inference. *Journal of Econometrics*, **93**, 345–368.

Hanushek, Eric, & Woessmann, Ludger. 2012. Do better schools lead to more growth? Cognitive skills, economic outcomes, and causation. *Journal of Economic Growth*, **17(4)**, 267–321.

Hanushek, Eric A., & Kim, Dongwook. 1995. *Schooling, Labor Force Quality and Economic Growth.* NBER Working Paper 5399.

López, Ramón, Thomas, Vinod, & Wang, Yan. 1998. *Addressing the Education Puzzle: The Distribution of Education and Economic Reform.* World Bank Working Paper 2031.

Lucas, Robert. 1988. On the Mechanics of Economic Development. *Journal of Monetary Economics*, **22**(1), 3–42.

Lutz, Wolfgang, Cuaresma, Jesús Crespo, & Sanderson, Warren. 2008. The Demography of Educational Attainment and Economic Growth. *Science*, **319**, 1047–1048.

Mankiw, N. Gregory, Romer, David, & Weil, David N. 1992. A Contribution to the Empirics of Economic Growth. *The Quarterly Journal of Economics*, **107**(2), 407–437.

Mejía, Daniel, & St.Pierre, Marc. 2008. Unequal Opportunities and Human Capital Formation. *Journal of Development Economics*, **86**, 395–413.

Moav, Omer. 2005. Cheap Children and the Persistence of Poverty. *The Economic Journal*, **115**, 88–110.

Nelson, Richard R., & Phelps, Edmund S. 1966. Investment in Humans, Technological Diffusion, and Economic Growth. *American Economic Review*, **56**(1), 69–75.

Pritchett, Lant. 2001. Where Has All the Education Gone? *The World Bank Economic Review*, **15**, 367–391.

Rehme, Guenter. 2003. *(Re-)Distribution of Personal Incomes, Education and Economic Performance Across Countries.* in: Theo Eicher and Stephen Turnovsky, eds., Inequality and Growth: Theory and Policy Implications, Cambridge, MIT Press.

Rehme, Guenther. 2007. Education, Economic Growth and Measured Income Inequality. *Economica*, **74(295)**, 493–514.

Romer, Paul. 1990. Endogenous Technological Change. *Journal of Political Economy*, **85**(5), 71–102.

Roodman, David. 2006. *How to do xtabond2: An Introduction to Difference and System GMM in Stata.* Center for Global Development Working Paper 103.

Roodman, David. 2007. *A Short Note on the Theme of Too Many Instruments.* Center for Global Development Working Paper 125.

SalaiMartin, Xavier. 1997a. I just ran four million regressions. *American Economic Review*, **87(2)**, 178–83.

SalaiMartin, Xavier. 1997b. *I just ran four million regressions.* NBER Working Papers 6252.

Sauer, Petra, & Zagler, Martin. 2012. Economic Growth and the Quantity and Distribution of Education: A Survey. *Journal of Economic Surveys, forthcoming.*

Shin, Yongcheol. 2007. *Threshold Autoregressive Models in Dynamic Panels.* http://www.eea-esem.com/files/papers/EEA-ESEM/2007/2612/tdp2.pdf.

Young, Alwyn. 2012. *The African Growth Miracle.* NBER Working Papers 18490.

A APPENDIX

Table A.1: Sample coverage by region

Advanced Economies	1950-2005	Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States
Europe and Central Asia	1970-2005	Albania, Bulgaria, Poland
	1990-2005	Armenia, Croatia, Czech Republic, Estonia, Kazakhstan, Kyrgyzstan, Latvia, Lithuania, Moldova, Romania, Russia, Serbia, Slovak Republic, Slovenia, Tajikistan, Ukraine
East Asia and the Pacific	1950-2005	Philippines, Thailand
	1955-2005	China, Republic of Korea, Malaysia, Taiwan
	1960-2005	Fiji, Hong Kong, Indonesia, Singapore
	1970-2005	Brunei, Cambodia, Laos, Macao, Mongolia, Vietnam
South Asia	1950-2005	India, Pakistan, Sri Lanka
	1960-2005	Bangladesh, Nepal
	1970-2005	Maldives
Middle East and North Africa	1950-2005	Cyprus, Egypt, Israel, Morocco
	1955-2005	Iran, Jordan, Malta
	1960-2005	Syria, Tunisia
	1970-2005	Bahrain, Iraq, Kuwait, Qatar, Saudi Arabia
	1990-2005	Yemen
Sub-Saharan Africa	1950-2005	Mauritius, South Africa, Uganda
	1955-2005	Ghana, Kenya, Malawi, Zambia, Zimbabwe
	1960-2005	Benin, Botswana, Burundi, Cameroon, Central African Rep., Republic of Congo, Ivory Coast, Gabon, Gambia, Lesotho, Mali, Mauritania, Mozambique, Namibia, Niger, Rwanda, Senegal, Tanzania, Togo
	1970-2005	Dem. Rep. Congo
Latin America and the Caribbean	1950-2005	Argentina, Bolivia, Brazil, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Guatemala, Honduras, Mexico, Panama, Peru, Trinidad & Tobago, Uruguay, Venezuela
	1955-2005	Chile, Jamaica, Paraguay
	1960-2005	Barbados
	1970-2005	Belize

B APPENDIX

We present OLS and fixed effects (FE) estimates for our main results in tables B.1 and B.2. The results are qualitatively similar to the GMM estimation, with a positive coefficient for the average years of schooling and a negative coefficient on the interaction term, giving further evidence for the robustness of our results. OLS and FE nicely reveal the pattern in the presence of dynamic panel bias. The coefficients on the lagged dependent variable are biased upwards (towards zero) in OLS estimation while they are strongly biased downwards when applying the fixed effects estimator. These thus put a lower and upper bound to good estimates of the true parameter (also noted by Roodman, 2006).

Table B.1: OLS estimates

	$\Delta y_{i,t}$			
	(1)	(2)	(3)	(4)
$\ln(y_{i,t-\tau})$	-0.027	-0.027	-0.027	-0.034
	(0.007)***	(0.006)***	(0.007)***	(0.007)***
$\Delta k_{i,t}$	0.465	0.466	0.466	0.470
	(0.025)***	(0.025)***	(0.025)***	(0.025)***
$\Delta n_{i,t}$	-0.200	-0.095	-0.095	-0.023
	(0.100)**	(0.106)	(0.109)	(0.113)
$\ln(S_{i,t})$	0.058		0.001	0.115
	(0.013)***		(0.028)	(0.055)**
$G_{i,t}$		-0.205	-0.202	0.071
		(0.042)***	(0.088)**	(0.144)
$\ln(S_{i,t}) * G_{i,t}$				-0.114
				(0.048)**
R^2	0.33	0.33	0.33	0.33
N	1,179	1,179	1,179	1,179

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard errors in parenthesis. Time dummies are included for each 5-year time interval of the sample period from 1950 to 2005.

Table B.2: Fixed effects estimates

	$\Delta y_{i,t}$			
	(1)	(2)	(3)	(4)
$\ln(y_{i,t-\tau})$	-0.237	-0.226	-0.237	-0.249
	(0.015)***	(0.016)***	(0.015)***	(0.016)***
$\Delta k_{i,t}$	0.396	0.388	0.394	0.399
	(0.027)***	(0.027)***	(0.027)***	(0.027)***
$\Delta n_{i,t}$	0.319	0.196	0.337	0.401
	(0.144)**	(0.145)	(0.145)**	(0.146)***
$\ln(S_{i,t})$	-0.189		-0.214	0.092
	(0.029)***		(0.040)***	(0.109)
$G_{i,t}$		0.398	-0.130	0.505
		(0.107)***	(0.144)	(0.255)**
$\ln(S_{i,t}) * G_{i,t}$				-0.268
				(0.089)***
R^2	0.38	0.37	0.38	0.39
N	1,179	1,179	1,179	1,179

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard errors in parenthesis. Time dummies are included for each 5-year time interval of the sample period from 1950 to 2005.