The Effects of Different Stages of Education on Income across Countries*

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Abstract

This paper provides cross-country panel estimations of the returns to the stages (primary, secondary, and tertiary) of education using an aggregate production function approach. In the production function, the human capital is modeled in the Mincerian way to obtain a log-linear equation. To take into account the likely heterogeneity among countries, we create subsamples of countries based on their development level and the quality of the schooling. Our estimates from various methods point to heterogeneous impacts of schooling (by levels) across countries. In particular, tertiary schooling seems to have a more important effect in countries with higher level of development and schooling quality, while primary (and secondary) schooling seems to play a more important role in relatively less developed countries with lower schooling quality.

Keywords: Education, human capital, cross-country studies, panel data methods
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It is simply not possible to have the fruits of a modern agriculture and the abundance of modern industry without making large investments in human beings.
-Theodore W. Schultz (1961, p. 16)

1 Introduction

The human capital, mainly referring to all worker characteristics that can potentially increase the productivity and efficiency in the production process, has been one of the most important ingredients of the economic modeling. Acemoglu (2009) contends that the human capital theory forms the basis of much of the labor economics field. In this vein, the positive impact of human capital on individual earnings has been demonstrated many times in the labor economics literature (e.g. see the survey by Card (1999)). According to such studies, the pre-labor market investments in schooling potentially boost the individual earnings through increasing the productive skills.[1,2] Taking the broad description of this form of capital, the aggregation implies that the human capital can possibly take a (small or large) role in the productivity of a country. Hence, macroeconomics studies as well rely very much on the notion of human capital.

Similar to the labor economics literature, the importance of the human capital has been often emphasized in the growth theories as well. Along these lines, enormous amount of theoretical and empirical research has been conducted to understand the income and growth rate differences across nations assigning a great role to the human capital and to deduce policy implications for further development of the laggard countries. The main motivation for such studies is the possible economy-wide externalities implied by the human capital investments, notably in the form of educational attainment. The idea is that the returns to such investments

[1] In the remaining of the paper, we focus on the educational attainment as the form of human capital, unless it is stated otherwise.

[2] There is a fundamental objection to this statement based on the signaling value of education saying that the returns to schooling may not necessarily reward the productive skills of the individuals, but rather it may reward the diplomas achieved. Another serious objection comes from the ability bias argument, which says that the returns to education may be higher for individuals with higher abilities, since they tend to attain more years of schooling as it is more convenient for them. This paper has no ambition to bring a concrete solution to this decades-old-debate. However, few remarks are needed for the continuation. Concerning the economy-wide estimations of the returns to education, the signaling aspect is rather hard to defend, as it would imply a systematic over-rewarding of schooling in the aggregate. In this vein, Topel (1999) asserts as follows: "Though signaling models of schooling imply that the private returns to schooling can exceed the social returns, empirical evidence for important signaling effects is at best meager." Concerning the ability argument, in the empirical applications, the downward bias implied by the measurement errors of the educational variables are offset by the upward ability bias (Card (1999)).

are much more than pecuniary contributions to the individual incomes and are more noticeable when aggregated. For instance, the economists and the social scientists largely agree that the educational attainment is associated with decreased infant mortality, improved health and increased life expectancy, better parenting, increased political participation, less crime, more social cohesion, and so forth (Gradstein, Justman, and Meier (2005)). As the individual level studies cannot fully account for such large benefits of educational attainments, in a way, it is up to the macroeconomic studies to explore them.

Thereupon, the recent (empirical) economic growth literature has been heavily motivated by the strong relation between the economic performance of a country and the human capital in the form of formal schooling. In particular, beginning in the early 1990s, the growth literature has witnessed a rise of empirical studies based on the linkages between educational attainment and growth with the vast availability of cross-country data sets. Durlauf, Johnson, and Temple (2005) state that most of these empirical growth papers concentrate on the period after 1960, because it is mostly after this date when national accounts data started to become available for a large number of countries.[3] Among such widely used datasets, the various versions of the Penn World Table and the educational attainment data of Barro and Lee (1993) have been the main data sources triggering numerous empirical growth papers in the subsequent decades. This great wave of cross-country empirical studies has been one of the main motivations of our paper.

Given the potential role of human capital on the economic development, in this paper, we are interested in studying the differences of the economic performances of the countries (including under-developed, developing, and developed) with a special focus on the (stages of the) educational attainment.[4] We think that the countries that are at various points of the development spectrum do not have a uniform benefit by arbitrarily increasing the educational attainment, coupled with the issue that various stages of educational attainment may have different impacts in different economic settings. Despite this aspect, it is very common in the literature to aggregate all levels of schooling across countries and see the impact on the economic performance. In a way, such papers do not recognize the difference of a one year increase, say, in the average years of primary school versus a one year increase in the average years of tertiary school on the macroeconomic outcomes. In our opinion, not only different stages of education by themselves have differential impacts on economic growth, but also these impacts may have different implications in different contexts.

Correspondingly, many papers in the literature have provided estimates of the impact of

[3]According to Durlauf, Johnson, and Temple (2005), another reason for choosing 1960 as the starting point is that many colonies started to gain independence around that date.

[4]Although we are aware that the notion of human capital investment encompasses many other forms such as on-the-job training, health improvements, and learning-by-doing, we choose to focus on formal schooling as the main form of human capital due to data constraints at a cross-country level.

education on the economic performance (e.g. on aggregate income, growth rates, etc.) based on different theoretical tools and using different econometrics methods with various datasets. Many of these papers have not yielded definite results on the role of education (e.g. Benhabib and Spiegel (1994), Islam (1995), Temple (2001), and so on). With respect to the majority of empirical growth papers, our approach is based on the Mincerian method of estimating returns to education, which has been commonly used at micro level labor studies, but rarely applied across countries. Even among the papers that have taken the Mincerian approach, the differential impacts of the different stages of education are not taken into account. To this end, we write a macro version of the individual level Mincer type of income equation by modeling the different stages of schooling in a piecewise linear form. In the standard micro-Mincer human capital earnings function approach, the coefficient in front of the education variable (i.e. years of schooling) gives the potential increase in the earnings due to one additional year of schooling. Parallel to this approach, we apply the Mincerian function to the countries, obtaining an extended macro-Mincer equation, which can potentially give the effect of a one-year increase in the average years of a given level of education on the income per capita across countries.

Another important issue that we emphasize is the prevailing differences among the countries, which makes it difficult to write models that put the countries of different economic experience, institutional structure, and development levels in one single estimating equation. For instance, in the specific context that we are in, the schooling quality of a country, where education takes place, might play a key role in determining the returns to schooling. In this vein, while many studies leave the quality dimension of the schooling untouched and act as if one year of schooling is uniformly the same across countries, we incorporate the differences in this dimension of schooling in our analysis.

Regarding the aforementioned issues on the differential role of stages of education, in this study, we precisely address the following questions: what are the effects of different stages of education (primary, secondary, and tertiary) on per capita income? How does the answer to this question change when the differences in the quality of the schooling and the development level of the countries are taken into account? What types of education seem to matter more (i.e. bring higher returns) and for what types of countries? Our estimation results for the whole set of countries (i.e. not distinguishing between developed or developing etc.) mainly indicate that when education is disaggregated into its levels, only the tertiary education has the highest (and significant) effect on the income per capita, while the estimates for the primary and secondary education are not significant. However, when we divide the countries into subsamples based on the development level and the quality of schooling, we get that, in general, more developed countries seem to benefit more from higher levels of education, whereas less developed countries seem to benefit more from early stages of education. Moreover, there is somewhat evidence suggesting that the impacts of schooling on aggregate income are influenced by the quality of education.

The plan of the paper is as follows: Section 2 details some of the important aspects of modeling the link between education and income; Section 3 describes the model and the empirical specification; Section 4 presents the data and the estimation results; Section 5 concludes. Lastly, the appendix gives further summary statistics about the data.

2 Some Important Aspects of Modeling Education

In this section, we draw attention to some of the essential points to take into account when thinking about how to model the link between education and income. First, we discuss why it is important to disaggregate educational attainment into its stages. Then, we highlight the importance of the international differences in the educational quality.

2.1 Levels of Education

Since the availability of the international educational attainment datasets (such as Barro and Lee (1993)), many empirical (growth) papers have used the educational variables measured by the (average) total years of schooling attained as a proxy for the human capital stock in a country. A common practice in these studies is to assess the impact of, among other factors, an additional year of schooling in the aggregate human capital stock on the aggregate income and/or growth. As Wössmann (2003) contends, in this case, an implicit assumption is that an additional year of educational attainment increases the human capital stock by an equal amount without distinguishing whether that additional year corresponds to an additional schooling attainment at the elementary level or at the university level.[5] This assumption, in turn, might lead one to miss part of the picture regarding the heterogeneous impacts of educational attainment on the economic outcome of a country. Therefore, to judge the role of educational attainment more comprehensively, it is important to look at the impacts of the composition of education.

Furthermore, in an endogenous growth framework, where the economic growth is contingent to (the composition of) the human capital and to the distance from the technological frontier, Aghion, Meghir, and Vandenbussche (2006) acknowledge the differing functions of the types of education in countries at different levels of development. Accordingly, lower levels of education stimulates adoption and imitation behavior when the country is far from the technological frontier, while higher levels of education triggers innovation when the country is closer to the frontier.[6] However, the estimations of Aghion, Meghir, and Vandenbussche

[5]See footnote 9 for more details on Wössmann (2003).

[6]The results of Aghion, Meghir, and Vandenbussche (2006) and our estimates seem to point towards the same direction in the sense of emphasizing differing effects of stages of human capital, yet the

(2006) are limited only to the OECD countries and leave out the quality dimension of the schooling, an issue of great importance, to which we now turn.

2.2 Quality of Education

A common approach taken by the majority of the papers in the empirical growth literature is that the commonly used human capital measures are almost always based on the quantitative aspects of education (e.g. school enrollment rates, years of schooling). At a first glance, this is mainly due to data availability. In many contributions, Hanushek and some other authors emphasize the quality issues that have often been neglected in the empirical growth literature. In this framework, the quality refers to the education quality in the form of knowledge that is inherent in the individuals (or the labor force). Therefore, any difference in the quality of education is directly reflected into the difference in the labor force, which in turn influences the economic performance of a country. Hence, the schooling quality differences might generate cross-country heterogeneity. In this vein, Hanushek and Kimko (2000) and Hanushek and Wössmann (2007) argue that by ignoring the quality differences in schooling, the vast cross-country empirical growth literature implicitly assumed that a year of education at a school in a very poor and isolated country is the same as a year of education at a school in a developed country. Moreover, as mentioned by Krueger and Lindahl (2001), too, "differences in the quality of education among countries with a given level of education affect the speed with which new technologies are adopted or innovated." Therefore, it is essential to recognize that one year of schooling does not raise the human capital stock by an equal amount regardless of the quality of the education system in which it takes place.

To take into account the qualitative differences in schooling across countries, there have already been several common and indirect measures of quality such as the class size, the pupil-teacher ratio, and the share of education expenditures in GDP. However, the empirical evidence found by Hanushek and Kimko (2000) implies that school resources are not strongly related to quality. In other words, they argue that cognitive skills of a population are not well-proxied by measures of school quantities or measures of resources devoted to schools. To this end, they suggest a more convenient proxy for schooling quality. Namely, they construct a comparable index of (labor force) quality based on direct international test scores, which measures the cognitive skills of the students for a number of countries that participated in those tests. Even though these tests include many other subjects, Hanushek and Kimko (2000) decide to focus on the mathematics and science scores. The reason for this, they argue, is that the mathematics and science scores are ultimately linked to the R&D activities. Accordingly, they assert that "able students with a good understanding of mathematics and science form a pool of future engineers and scientists," which in turn plays an important role in terms of

underlying models are very different.

R&D activities as a source of growth as in the endogenous growth models.[7]

At this point, one might come up with several objections regarding the direction of causality from the quality towards growth. First, the quality of schooling may be endogenous to the development level of a country. Put differently, there might potentially exist reverse causality from the level of development towards the schooling quality, since richer countries might invest more in educational inputs and boost the performance of the test scores of the students. Hanushek and Kimko (2000) check this possibility by running additional regressions of the test scores on the per capita income levels and the schooling inputs. Their results find no evidence of reverse causality, which leads them to conclude that the causality concerns of schooling quality and economic performance are not worrisome. Second, there might be some omitted variables, which can potentially influence both the test scores and the economic performance, creating a spurious relation. To deal with this point, Hanushek and Kimko (2000) look at the immigrants living in the U.S. and try relate the variations in their earnings to the quality measures. Accordingly, they find that immigrants who were schooled in countries with higher scores on these tests have higher earnings in the U.S., whereas there is no earnings advantage for the immigrants receiving part or all of their schooling in the U.S.

3 Model

3.1 Contribution to Literature

Having explained the importance of several aspects when modeling the link between education and income, now we come back to the main issues and contribution of the current paper. The goal of this paper is to estimate the impact of properly specified human capital (in the form of formal education) on the output per worker, which is a very close proxy for the income per capita in a given country, and ultimately on the economic growth, taking a parametric aggregate production function approach.[8] Surely we acknowledge the fact that formal schooling is not the only form of human capital (other complementary forms such as on-the-job training, learning-by-doing, improvement in health status, increased life standards and expectancy, and so forth are clearly important to the formation of human capital), but beside the data availability issues, we believe that formal schooling still constitutes the majority of the human capital formation.

[7] In a seminal contribution, Murphy, Shleifer, and Vishny (1991) show that countries with a larger fraction of engineers with respect to the fraction of lawyers experience higher growth rates, for the latter group is involved more with rent-seeking activities, which in turn reduces growth.

[8] Griliches (1997), as well, points out that perhaps the most appropriate way to gauge the impact of human capital –namely schooling– on the aggregate income is to include it as an input in an aggregate production function.

Concerning the human capital measures, initial contributions to the literature have made use of the school enrollment rate (a flow variable) and mostly the estimations render non-significant coefficient estimates. Another problem associated with enrollment rate is that it might overcount the grade repeaters and ignore the dropouts. On the contrary, according to Card (1999) and Wössmann (2003), the Mincerian way of taking years of schooling is the best fit to the data linking earnings (income) to schooling. Therefore, inspired by the labor economics studies, in estimating the impact of schooling on the aggregate income, we take the years of schooling as the measure of human capital (stock). This allows us to obtain a log-linear relation between the years of schooling and income, as it will be explained in the empirical specification.

However, as discussed in detail in the previous section, we believe that one year of schooling does not raise the human capital stock by an equal amount regardless of whether it is a person's first or fifteenth year of schooling. Therefore, we disaggregate the education into its various stages (primary, secondary, tertiary) using the latest data available. This is an important point to take into account, since many papers in the literature (especially the ones that use average years of schooling as the proxy for human capital) implicitly assign the same weight to any year of schooling attained. On top of this, by disaggregating the education into its stages, one can check whether there are decreasing effects of education (by levels) or any possible nonlinear pattern as found in numerous micro-level studies.

What is more, we argue that the impact of different stages of education on the income (and hence on growth) might depend on the level of development and quality of schooling of a country. For instance, it might be that lower levels of education may play a more important role for poor countries and/or the returns to education might be lower in countries where the quality of education is low. In that sense, Aghion, Meghir, and Vandenbussche (2006) also stress the importance of the heterogeneous effects of human capital on the economic performance of the countries and say that "the possibility that human capital might play a different role at different stages of development has not often been addressed in the empirical growth literature." Hence, while there are few papers that considered the disaggregated version of human capital variables, most of the time these papers do not incorporate the schooling quality dimension or they do not model the human capital à la Mincer (hence finding insignificant and/or negatively signed effects). Our contribution to the literature is that we incorporate all such aspects together when we estimate the effect of schooling in an aggregate production function.[9]

[9] An exception of incorporating both the stages and the quality of education is Wössmann (2002, 2003). However, he does not conduct the same exercise of estimating the impacts of various stages of education on the aggregate income as we do. Instead, he conducts a development accounting exercise, where he tries to see to what extent the variation in the properly specified factor inputs (especially human capital) and the total factor productivity can account for the variation in the aggregate output

When studying the effect of education on output per worker, to deal with the existing heterogeneity among the countries, we create subsamples of countries based on the level of development and the quality of schooling in a given country.[10] We measure the level of development by the average GDP per worker over the period of study (i.e. 1960-1990). The schooling quality is measured by the internationally comparable test scores (mathematics and science) of the students in various countries as provided by Hanushek an Kimko (2000) and Wössmann (2003). There are several reasons why we choose these two dimensions for the classification of countries. Firstly, having higher income levels does not necessitate having higher quality of schooling, although there might exist some overlaps. Hence, it is worth to distinguish between the two. Secondly, given our context of seeing the effects of education on income of countries, it makes sense that we include the quality of education as another dimension to incorporate the heterogeneity.

Furthermore, with the availability of larger cross-country data over time, we opt to use a panel data. In particular, we use the output, capital, and recently updated educational attainment data for the 1960-1990 period.[11] With respect to the papers using cross-section data, our use of panel data surely carries more information in the time dimension, which in turn helps improve the precision of the estimates. Additionally, Aghion, Meghir, and Vandenbussche (2006) advocates the use of panel data techniques and instrumentation methods to deal with the endogeneity and/or reverse causality issues (i.e. the possibility that having a higher income/growth prospect might boost educational attainment).

3.2 Empirical Specification

Whilst there is a long debate on what functional form of the human capital to adopt in empirical growth specifications, Cohen and Soto (2007) contend that the measure of human

at a point in time (namely, in 1990). While doing this, Wössmann (2002, 2003) plugs in the already estimated rates of return to stages of education obtained from the microeconometrics studies for various countries as surveyed in Psacharopoulos (1994) and he interacts the quality index of the schooling with the years of schooling at different stages. His analyses indicate that the properly specified human capital variables are able to account for more than half of the international output variation (much higher results are found for OECD countries), a result which is in sharp contrast with Hall and Jones (1999) and Klenow and Rodriguez-Clare (1997a), who find greater role attributed to the total factor productivity.

[10] Durlauf and Johnson (1995) apply the regression tree method to endogenously create country subsamples based on the initial conditions (income and literacy rate). They assert that the regression tree method helps to identify the multiple regimes that prevail in the data among countries and each subsample has its own production function, which overall implies a piecewise linear model for the whole sample.

[11] Except for few recent papers, the majority of the empirical growth papers cover the period of 1960-1985 or 1965-1990.

capital based on Mincer has recently gained eminence in the macro growth literature.[12] In his seminal contribution, Mincer (1974) relates the logarithm of individual earnings to the educational attainment and experience with its square. Krueger and Lindahl (2001) suggest that a similar approach can be adapted at a macro level.[13]

First, we start with the following Cobb-Douglas aggregate production function assuming an output-augmenting technological progress:

$$Y_{it} = A_{it} K_{it}^{\alpha} H_{it}^{1-\alpha}, \tag{1}$$

where Y_{it} denotes the total output (a proxy for the aggregate income), A_{it} is total factor productivity, K_{it} is the aggregate physical capital, and H_{it} is the aggregate human capital. As in the usual notation, i indexes country and t indexes time. The per worker variables are denoted by small letters, i.e. $y_{it} = Y_{it}/L_{it}$, $k_{it} = K_{it}/L_{it}$, and $h_{it} = H_{it}/L_{it}$, where L_{it} denotes the labor force. Moreover, under the assumption of a competitive economy, where each input earns its marginal product, α and $(1-\alpha)$ respectively denote the shares of physical and human capital in the national income.

As we are interested in the productivity effect of the human capital input (i.e. education), we derive the output per worker by dividing both sides of Eqn. (1) by the total labor force:

$$\begin{aligned} \frac{Y_{it}}{L_{it}} &= A_{it} \left(\frac{K_{it}}{L_{it}}\right)^{\alpha} \left(\frac{H_{it}}{L_{it}}\right)^{1-\alpha} \\ y_{it} &= A_{it} k_{it}^{\alpha} h_{it}^{1-\alpha}. \end{aligned} \tag{2}$$

Taking the natural logarithm of Eqn. (2) yields:

$$\ln y_{it} = \ln A_{it} + \alpha \ln k_{it} + (1-\alpha) \ln h_{it}. \tag{3}$$

Hence this specification writes the natural logarithm of output per worker as a function of the natural logarithms of total factor productivity and physical and human capital per worker. Next, we assume that the natural logarithm of total factor productivity consists of a country fixed effect (η_i), a time effect (δ_t), and a random disturbance (ε_{it}) that varies over time:

$$\ln A_{it} = \eta_i + \delta_t + \varepsilon_{it}. \tag{4}$$

[12] For example, among the papers that use the Mincerian approach in the empirical growth literature are Klenow and Rodriguez-Clare (1997a), Hall and Jones (1999), Topel (1999), Soto (2002, 2008), and so forth.

[13] At first glance, one may miss the correspondence between the aggregate income equation and the Mincerian earnings equation, because the former uses the logarithm of the GDP per capita (or output per worker) as the dependent variable, while the latter uses the mean of log earnings. However, Krueger and Lindahl (2001) assert that when the aggregate production function is Cobb-Douglas, the link between the macro-Mincer and the GDP equation plausibly holds.

Note that with this formulation, it is assumed that there is common technological progress for all the countries.

As suggested by the empirical labor economics literature, when modeling the link between educational attainment and income, one of the best fits to the data is given by the Mincerian earnings function method. In order to obtain a Mincerian log-linear relation between the income per capita and the years of schooling from an aggregate production function, it is necessary that the human capital input be an exponential function of the years of schooling. Thus, we model the aggregate human capital stock as follows:

$$H_{it} = \exp\left(\Phi(S_{it})\right) L_{it}, \tag{5}$$

where S_{it} is –for now– a composite of the average years of overall educational attainment.[14] The implied human capital per worker is:

$$h_{it} = \exp\left(\Phi(S_{it})\right). \tag{6}$$

Then, we additively decompose education into its three stages (i.e. $\Phi(\cdot) = \phi_1(\cdot)+\phi_2(\cdot)+\phi_3(\cdot)$):

$$h_{it} = \exp\left(\sum_{j=1}^{3} \phi_j(S_{jit})\right), \tag{7}$$

where S_{jit} denotes the average total years of schooling of country i at t for the stage $j =$ 1 (primary), 2 (secondary), and 3 (tertiary) of education. We assume linearity for the $\phi_j(\cdot)$ functions:

$$h_{it} = \exp\left(\sum_{j=1}^{3} \beta_j S_{jit}\right). \tag{8}$$

Next, we plug in the total productivity and human capital formulations into Eqn. (3) to get:

$$\ln y_{it} = \alpha \ln k_{it} + (1-\alpha)\left[\sum_{j=1}^{3} \beta_j S_{jit}\right] + \eta_i + \delta_t + \varepsilon_{it}. \tag{9}$$

Hence, we obtain a log-linear (or semi-log) relation between the aggregate income and years of schooling (rather than a log-log specification). In this case, the coefficient $(1-\alpha)\beta_j$ in front of years of schooling at stage j should be interpreted as the–possibly causal–effect (or return) of an additional year to the average years of schooling at stage j (or simply the effect of schooling at stage j) on GDP per worker and ultimately on growth. We note that the coefficient β_j by itself is just the effect of an additional year of schooling attainment at stage j on the human capital per worker in Eqn. (8).

[14] Although experience (and its square) is an inevitable variable of the micro-level Mincerian equations, we do not take it into account in our estimation and focus only on the schooling. Soto (2002) includes the experience term in his human capital specification, but the results do not change by much.

Due to the Cobb-Douglas specification, the Eqn. (9) imposes the coefficients α and $1-\alpha$ in front of the input variables of the production. However, we can rewrite the Eqn. (9) in an unconstrained form as:

$$\begin{aligned} \ln y_{it} &= \pi_k \ln k_{it} + \pi_s \left[\sum_{j=1}^{3} \beta_j S_{jit} \right] + \eta_i + \delta_t + \varepsilon_{it}, \\ \ln y_{it} &= \pi_k \ln k_{it} + \pi_{1s} S_{1it} + \pi_{2s} S_{2it} + \pi_{2s} S_{3it} + \eta_i + \delta_t + \varepsilon_{it}, \end{aligned} \tag{10}$$

where π_k and π_{js}'s (with $\pi_{js} \equiv \pi_s \cdot \beta_j$, main parameters of interest) are the effects of the physical capital and educational attainment by levels on output per worker, respectively.

Our estimation procedure is based on several methods. To estimate Eqn. (10), we start with Ordinary Least Squares (OLS) and fixed effects methods. However, we are aware that these methods do not correct for likely biases on the estimates that might originate from the measurement errors and endogeneity of the explanatory variables. In this vein, Bond, Hoeffler, and Temple (2001) assert that "the potential for obtaining consistent parameter estimates even in the presence of measurement error and the endogenous right-hand side variables is a considerable strength of the GMM (Generalized Method of Moments) approach in the context of empirical growth research." Therefore, we continue our estimations with more involved panel data estimation methods, such as Arellano-Bond and System Generalized Method of Moments (System GMM). Concerning the latter methods, with respect to the classical Arellano-Bond method, the additional feature of System GMM is that the equation in first differences are estimated simultaneously with the levels equation and thus additional instruments can be employed with the use of the levels equation as in the following system:[15]

$$\begin{aligned} \ln y_{it} &= \pi_k \ln k_{it} + \pi_{1s} S_{1it} + \pi_{2s} S_{2it} + \pi_{3s} S_{3it} + \eta_i + \delta_t + \varepsilon_{it}, \\ \Delta \ln y_{it} &= \pi_k \Delta \ln k_{it} + \pi_{1s} \Delta S_{1it} + \pi_{2s} \Delta S_{2it} + \pi_{3s} \Delta S_{3it} + \Delta\delta_t + \Delta\varepsilon_{it}. \end{aligned} \tag{11}$$

The procedure in both of these methods is to instrument the endogenous variables with properly chosen lags of the explanatory variables and the lags of their first differences. More precisely, while the Arellano-Bond method estimates the equation in first differences by instrumenting it with the levels of explanatory variables lagged twice or more, the System GMM method estimates additionally the levels equation by instrumenting it with the lagged first differences of the explanatory variables.

Furthermore, as known, the consistency of the GMM estimation depends on the validity of the instruments and the lack of serial correlation in the residuals, both of which can be tested. To test for the first condition, we use a Sargan test of over-identifying moment restrictions.

[15]The System GMM requires an assumption regarding the initial conditions of the system, but such a restriction is plausibly satisfied by empirical growth literature. For further details on the application of these methods in the empirical growth literature, see Bond, Hoeffler, and Temple (2001).

For the second issue, we use Arellano-Bond's test for serial correlation in the error terms. The p-values for these tests are included at the bottom of the estimation tables. We report the estimation results in Sections 4.3 and 4.4.

4 Estimations

4.1 Data

Our estimates are based on the dataset on education, output, and capital stock provided by Cohen and Soto (2007). The educational attainment data of Cohen and Soto (denoted *CS*, thereafter) covers 94 countries[16] and is described in more detail in Cohen and Soto (2007).[17] Mainly, CS data provides information on the percentage of the population aged 15 and above and population aged 25 and above without schooling, with primary schooling (complete and/or incomplete), secondary schooling (complete and/or incomplete), and tertiary schooling (complete and/or incomplete). CS data also gives the cross-country census information regarding the duration of the years of schooling by educational levels. Using these data allows us to compute the years of schooling attained by educational levels for each country between 1960-1990 (see Table 1). The output data is a cross-country panel based on the version 5.6 of the Penn World Table[18] covering the same period. The physical capital data of Cohen and Soto (2007) is originally taken from Easterly and Levine (2001). As the education data of CS is constructed by 10-year intervals (hence, $T = 4$), both the output and physical capital data are reported by 10-year intervals. Overall, the final sample (we call it the *CS sample*) is an unbalanced panel with 376 country-year pairs.

Finally, the education quality data (time-invariant) is provided by Hanushek and Kimko (2000) and Wössmann (2003), where the latter author reports both observed and imputed values of the schooling quality index for a much larger set of countries.[19]

[16] The original CS data includes 95 countries; however, to match the educational attainment data with the educational quality data, we drop Cuba, for which we do not have the schooling quality index.

[17] Cohen and Soto (2007) discuss in detail the improvement from the measurement error issues with respect to the several other datasets. Meanwhile, although their education data covers the period 1960-2010 (with projections for 2010), their estimations are based on the period 1960-1990 for comparability with the majority of the papers in the empirical growth literature. The data is available at the following link: http://soto.iae-csic.org/Data.htm

[18] The Penn World Table includes annual and internationally comparable data on output (appropriately adjusted for the purchasing power parity), population, labor force, investment, and so forth beginning in the 1950s.

[19] More specifically, the imputation procedure is as follows: using quality index data of Hanushek and Kimko (2000) of 65 countries, Wössmann (2003) takes the mean of the respective regional average

Table 1: Descriptive Statistics: Years of Educational Attainment by Levels

	No. of Obs.	Mean	Stand.Dev.	Min	Max
Primary education (15+)	376	1.787911	1.07757	0.032743	5.50228
Secondary education (15+)	376	2.459899	2.273109	0.0057603	9.431778
Tertiary education (15+)	376	0.6474553	0.8215172	0	5.081615
Total years of education (15+)	376	4.895265	3.216765	0.0545301	12.32269
Primary education (25+)	376	1.789238	1.196409	0.0293006	5.425602
Secondary education (25+)	376	1.893248	2.065935	0	9.100007
Tertiary education (25+)	376	0.7221706	0.9210138	0	5.588048
Total years of education (25+)	376	4.404656	3.229513	0.0523398	12.44395

Notes: The total years of schooling attained at each level of education is computed using the percentage of population having attained a given level of education and the census information giving the duration in years of each educational level in each country. All the data is taken from Cohen and Soto (2007). The total years of education is the sum of the years of the three levels of education attained.

The former quality data covers 65 countries, while the latter covers much more than the countries in the CS sample (except for Cuba). Therefore, our main estimations make use of the latter quality index in order to cover a larger set of countries.

4.2 Country Classification

Our working hypothesis is that given the potential heterogeneity among countries, the judgment on the impact of education on income across countries might miss to see part of the picture if it does not additionally consider the possibly differing effects education (and its different stages) may have at different types (in terms of level of development, the quality of the education provided, and so on) of countries. In this vein, we propose a country classification based on the level of development and/or the schooling quality of a country. This is in close line with the approach of multiple (growth) regimes across countries suggested by Durlauf and Johnson (1995) and Durlauf, Johnson, and Temple (2005). Intuitively, this approach points to different return patterns or regimes that might exist between education and aggregate income per capita across countries.

More precisely, we measure the level of development by the average (logarithm of) output per worker (proxying per capita income) over 1960-1990. The schooling quality index is from Wössmann (2003), based on the internationally conducted tests

and the respective income group average for any country with a missing quality index, where the classification of countries by major regions and income groups is based on World Bank (1992).

to students. After analyzing the distribution of the average output per capita and the schooling quality index across countries (see Table 2), we pick relevant cutoff points for these two indicators. As a simple illustration, let y^* and q^* be the chosen cutoff points for the average output per worker and schooling quality index, respectively. An example classification could be to allocate a country i into Class 1 if $y_i > y^*$ and $q_i > q^*$ and into Class 3 if $y_i < y^*$ and $q_i < q^*$. The remaining countries (if any) are allocated into Class 2. We also try simpler classifications based only on the quality of schooling index, which is strongly associated with the development level. In this case, we pick one q^* (could be the median, mean, and so on of the time-invariant q distribution) and then designate that the countries above q^* are in Class 1 and vice versa.

Table 2: Descriptive Statistics: Schooling Quality and Mean Output

	No. of Countries	Mean	Median	Stand.Dev.	Min	Max
q	94	0.9309255	0.892	0.2461947	0.39	1.542
$\ln \bar{y}$	83	8.788214	8.89294	0.9774275	6.434523	10.32463

Notes: q denotes the schooling quality index from Wössmann (2003), which is originally based on Hanushek and Kimko (2000). $\ln \bar{y}$ is the logarithm of the average output per worker (in 1985$) in the CS the sample over 1960-1990.

Overall, our estimations involve many classifications depending on the cutoff points chosen. In the estimation results, the cutoff points are noted at the bottom of each table. Moreover, to avoid that the results are driven by *ad hoc* classifications, we have tried many combinations of cutoff points for the average income and/or quality index (as long as the sample sizes are reasonable across different groups; otherwise, the smallest group is added to the next group); in almost all cases, our results remain rather robust.

4.3 Results for the Whole Sample

Initially, we estimate the levels equation in Eqn. (11) by OLS and fixed effects methods for the whole set of countries, without classification of any sort and without correcting for endogeneity problems.[20] Columns (1) and (3) in Table 3 give the OLS estimates. We see that an additional year to average years of tertiary education has, on average, a significant effect around 6.1-6.8% on aggregate income per capita for the whole set of

[20]In the rest of the paper, all the estimations control for physical capital, but are not reported in the tables, since we are interested in the parameter estimates in front of education variables (π_{js}'s). Nevertheless, the estimates of the coefficient of physical capital are in the range of $0.3 - 0.5$.

countries, while the primary and secondary education have small and negatively signed, yet insignificant effects. However, we know that there are many country specific effects that are not taken into account with the OLS method. To this end, we report the fixed effects estimates in columns (2) and (4). The fixed effects estimates yield significant and positively signed effects for each level of schooling on ouput per worker. Controlling for the primary and secondary schooling, the tertiary schooling again seems to be the most influential type of schooling, its significant effect on aggregate income per capita being in the range of 11.2-13.2%. What is more, in columns (2) and (4), among the three types of education, the secondary education seems to have the smallest effect, leading to a slight *V-type* of pattern of the effects of schooling.

Table 3: OLS and Fixed Effects Estimations

	(1) OLS	(2) Fixed Effects	(3) OLS	(4) Fixed Effects
Primary education (15+)	-0.0630	0.0643**		
	(0.0461)	(0.0297)		
Secondary education (15+)	-0.0057	0.0488**		
	(0.0215)	(0.0242)		
Tertiary education (15+)	0.0684*	0.1328**		
	(0.0352)	(0.0382)		
Primary education (25+)			-0.0444	0.0944**
			(0.0438)	(0.0290)
Secondary education (25+)			0.0008	0.0809**
			(0.0209)	(0.0250)
Tertiary education (25+)			0.0611*	0.1120**
			(0.0320)	(0.0314)
N	313	313	313	313
R^2	0.8940	0.8136	0.8925	0.8196

Notes: All estimations are based on the CS Sample and control for the year effects. Robust standard errors are reported in parentheses. * denotes significance at least at 10%, while ** denotes significance at least at 5%.

Next we estimate the same model by more involved panel data methods taking into account the likely endogeneity and measurement error problems. Namely, we estimate the effects of different levels of educational attainment on the output per worker using the Arellano-Bond and System GMM methods, as described briefly in Section 3. The results are reported in Table 4. Similar to the fixed effects estimates, the System GMM estimates yields significant effects only for the tertiary education. In particular, the estimates from columns (2) and (4) indicate that an additional year to the average years of tertiary educational attainment in a country implies 7.3-10.9% increase in the output per worker. The Arellano-Bond estimates for the same type of schooling yield 10-11% impact on output; however, the estimates are not statictically significant, albeit economically significant.

Table 4: Arellano-Bond and System GMM Estimations

	(1) Arellano-Bond	(2) Sys. GMM	(3) Arellano-Bond	(4) Sys. GMM
Primary educ. (15+)	-0.0012	-0.0152		
	(0.0617)	(0.0274)		
Secondary educ. (15+)	0.0066	-0.0063		
	(0.0400)	(0.0225)		
Tertiary educ. (15+)	0.1116	0.1092**		
	(0.0848)	(0.0338)		
Primary educ. (25+)			0.0470	-0.0338
			(0.0561)	(0.0291)
Secondary educ. (25+)			0.0589	0.0190
			(0.0505)	(0.0245)
Tertiary educ. (25+)			0.1058	0.0734**
			(0.0752)	(0.0282)
N	147	230	147	230
Serial Corr. (p-values)	0.1579	0.4709	0.1602	0.5630
Sargan (p-values)	0.2149	0.0984	0.2973	0.1513

Notes: All estimations are based on the CS Sample and control for the year effects. Robust standard errors are reported in parentheses. ** denotes significance at least at 5%. The first line of p-values come from testing the null hypothesis that the residuals are serially uncorrelated. The Sargan p-values come from testing the validity of additional (over-identifying) instruments.

As a consequence, concerning the role of education on aggregate income per capita, our basic results are still promising in the sense that we get positive and significant returns to (tertiary) schooling with respect to the indefinite and/or negative findings for educational attainment in the empirical growth literature. This convinces us further that the Mincerian specification improves the results to a greater extent. However, our estimations yield almost no significant effect of primary and secondary education on income, which might possibly play a role for less developed and developing countries–especially thinking of the leader-follower country argument proposed by Aghion, Meghir, and Vandenbussche (2006) as described briefly in Section 2. Moreover, it may be that putting 94 countries of different development levels, institutional structure, and schooling quality into the same estimating equation might lead to results that are not representative for all of them. Therefore, we turn to estimations with country classifications in order to see whether other types of education have significant and positive impact on output per worker across different groups of countries.

4.4 Results with Country Classifications

Our estimates of the effect of stages of education on aggregate income have mainly yielded relatively higher and mostly significant values only for the tertiary education (both for the educational attainment variable for population aged 15 and above and aged 25 and above) ranging between 6-13%. However, thinking of the role of the other types of educational attinment, it might seem surprising that they do not have any effect on output. It is here where we believe that a country classification might prove especially useful to help us diagnose returns to education patterns across countries.

Table 5: Fixed Effects Estimations

	(1) Class 1	(2) Class 2
Primary education	0.0929	0.0762
	(0.0729)	(0.0838)
Secondary education	0.0728	0.0615
	(0.0668)	(0.0414)
Tertiary education	0.1193*	0.0608
	(0.0613)	(0.1154)
N	137	176
R^2	0.8022	0.6088

Notes: The estimations control for year effects and use the educational attainment variable of population aged 25 and over. The robust standard errors are reported in parentheses. * denotes significance at least at 10%. A country i is allocated to Class 1 if $q_i > 0.95$ and Class 2 if $q_i < 0.95$.

In Table 5, we initially report the fixed effects estimates of the impacts of the levels of education on the output per worker for two classes of countries, where the relatively similar countries (in terms of the education quality) are allocated into the same class. In other words, Class 1 contains countries with higher schooling quality with respect to Class 2. Reading the output table, we get that the tertiary education has the highest and significant effect (11.9%) in Class 1 countries, whereas the primary education has the highest effect (7.6%) in Class 2 countries. Overall, despite some statistically insignificant estimates from fixed effects, the sign and the differing relative magnitudes between the levels of education across different sets of countries seems to point to varying patterns of the returns to the levels of education. Another interesting observation (yet, neither a uniform nor a general result) in Table 5 is that from columns (1) and (2), we see that the estimates, especially for tertiary education, in Class 1 countries are always higher than the estimates in Class 2 countries. Then, given the fact that the countries are classified according to their schooling quality, one way to interpret this difference in magnitudes is that the effects of levels of education appear to decrease when the quality of schooling is relatively lower.

Table 6: Fixed Effects Estimations

	(1) Class 1	(2) Class 2	(3) Class 3
Primary education	0.0783	0.0782	0.1224
	(0.0491)	(0.0533)	(0.0854)
Secondary education	0.0453	0.0704	0.1170**
	(0.0375)	(0.0502)	(0.0573)
Tertiary education	0.1352**	0.0740	0.0414
	(0.0520)	(0.0449)	(0.1231)
N	89	122	102
R^2	0.9342	0.8420	0.6413

Notes: The estimations control for year effects and use the educational attainment variable of population aged 25 and over. The robust standard errors are reported in parentheses. ** denotes significance at least at 5%. A country i is assigned to Class 1 if $q_i > 1.1$ and $\ln \bar{y}_i > 9.4$; Class 3 if $q_i < 0.8$ and $\ln \bar{y}_i < 8.5$; and Class 2 otherwise.

Next, in Table 6, we report the fixed effects estimates with a different classification that separates the countries into three groups, Class 1, Class 2, and Class 3, where, parallel to the first classification, the relatively similar countries (this time in terms of the mean of output per worker and education quality) are assigned to the same groups. In this table, Class 1 comprises of the countries with high average output per worker over 1960-1990 and schooling quality, while Class 3 comprises of the countries with relatively lower mean output per worker and schooling quality. Class 2 contains all the remaining countries in-between. From column (1) of Table 6, we see that the tertiary education has a significant and the highest effect (13.5%) on output in the Class 1 countries. On the contrary, it is the primary and the secondary educational attainment that have relatively higher effects, with secondary education having a significant estimate of 11.7% for countries belonging to Class 3. Lastly, for the countries in Class 2, our estimates yield effects around 7% for all levels of education.

Concerning the magnitudes of the effect of a given level of education on output per worker across classes in Table 6, we see that for tertiary schooling, the highest estimated parameter values belong to Class 1 countries. For primary and secondary schooling, on the other hand, the highest estimated parameter values belong to Class 3 countries. One possible interpretation of this result could be that the quality differences in education are more important at higher levels of education (e.g. tertiary) than the earlier levels (e.g. primary), perhaps because the former education stage involves more sophisticated knowledge accumulation than the latter. However, as we do not have the quality measure for different stages of education, but an aggregated index summarizing everything, we cannot say much on this issue. Overall, even with this different classification of the countries, our results suggest similar patterns concerning the heterogeneous effects of educational attainment by levels among countries.

Finally, we turn to the estimations using Arellano-Bond and System GMM methods with country classifications. In Table 7, we report the model estimates based on Arellano-Bond and System GMM methods with same two-part classification of countries as it is used in Table 5. As seen in columns (1) and (3), both Arellano-Bond and System GMM methods yields the highest and significant estimates for the tertiary education in Class 1 countries (9.4% and 4.04%, respectively). The estimates for other types of educational attainment are rather small in magnitude and not significant for countries in Class 1. On the contrary, as seen in columns (2) and (4), Arellano-Bond and System GMM methods yield relatively higher estimates for the primary education in Class 2 countries, 5.1% and 12.62%, respectively, with the latter estimate being significant at 5%. Concerning the impacts of the other levels of education on output in Class 2 countries, neither Arellano-Bond nor System GMM methods give significant and clear returns pattern. As a consequence, these last estimation methods also suggest heterogeneous effects of the levels of education across countries when the education quality differences are taken into account.

Table 7: Arellano-Bond and System GMM Estimations

	(1) Arellano-Bond Class 1	(2) Arellano-Bond Class 2	(3) Sys. GMM Class 1	(4) Sys. GMM Class 2
Primary education	0.0061	0.0510	-0.0088	0.1262**
	(0.0454)	(0.0621)	(0.0181)	(0.0311)
Secondary education	0.0250	0.0404	-0.0298**	0.0035
	(0.0360)	(0.0486)	(0.0075)	(0.0185)
Tertiary education	0.0940**	-0.0672	0.0404**	0.0542
	(0.0391)	(0.0921)	(0.0093)	(0.0479)
N	67	80	102	128
Serial Corr. (p-values)	0.8482	0.0775	0.3846	0.0949
Sargan (p-values)	0.0918	0.4918	0.2549	0.5153

Notes: All estimations are based on the CS Sample, control for the year effects, and use the educational attainment variable of population aged 15 and above. The robust standard errors are reported in parentheses. ** denotes significance at least at 5%. The first line of p-values come from testing the null hypothesis that the residuals are serially uncorrelated. The Sargan p-values come from testing the null hypothesis that the additional instruments are valid. A country i is allocated to Class 1 if $q_i > 0.95$ and Class 2 if $q_i < 0.95$.

5 Conclusion

In this paper, we have provided cross-country estimates of the effects of education by its levels on the output per worker. Our empirical specification is based on a macro-Mincer equation with an aggregate production function. To take into account the heterogeneities among the countries, we classified the countries into relatively homogeneous subsamples based on the criterion such as the schooling quality. Overall, our results point to heterogeneous effects of the levels of education on the aggregate income across countries. In particular, estimates from various panel data methods indicate that tertiary schooling seems to have a more important effect on aggregate income in countries with higher level of development and schooling quality, while primary and/or secondary schooling seems to have a more important effect on aggregate income in relatively less developed and/or developing countries with lower schooling quality. Thus, although many papers from the empirical macro-growth literature do not suggest a clear-cut estimate of the effect of the levels of education on aggregate income, our Mincerian method and classification approach with the use of an updated human capital stock data yield promising results.

Additionally, in numerous contributions to the returns to education literature, the surveys of Psacharopoulos (1981, 1994) and Psacharopoulos and Patrinos (2004) draw attention to the relevance of the different levels of education, providing extensive surveys of the individual level estimations of the rate of returns to education for a large set of countries. Even though our estimates cannot be directly compared to such studies for many reasons (for instance, our paper provides macro-level estimates, while they use micro-level estimates for countries), our results do not necessarily support their suggested general pattern such as the primary education having the highest returns across all countries. What is more, their conclusion that the returns to education are higher in relatively poorer countries (with potentially lower quality of education) might not necessarily be true if the quality dimension is taken into account, since the latter dimension might increase the returns from educational attainment.

As a final analysis, by suggesting areas of concentration in educational attainment, we believe that our results provide essential policy implications with the goal to increase the well-being of the society through investment, among other things, in education. For instance, as cited in Aghion, Meghir, and Vandenbussche (2006), Sapir et al. (2003) suggest that for European countries to decrease the productivity growth gap with respect to the US, the former countries should increase the educational investments at tertiary level. Moreover, concerning the less developed and developing countries, in addition to paying attention to the types of educational attainment that could boost aggregate income, another potential growth-enhancing strategy would be to improve the quality of education provided through investments in teachers. Finally, our estimates motivate further understanding of the mechanism regarding impact of education on economic growth taking into account the heterogeneous role of its levels coupled with the quality dimension. In that sense, the theoretical contribution of Aghion, Meghir, and Vandenbussche (2006) with the leader-follower type of argument is rather appealing.

Appendices

In this section, we provide additional descriptive statistics for the countries by classes. We start by reporting the countries that belong to the relevant group based on human capital quality index and the average output per capita for the classifications used in Tables 5-7. The next tables report the average years of educational attainment by levels of the countries for the classification used in Table 5-7. As before, the total years of schooling at each level of education is computed using the percentage of population having attained a given level of education and the census information giving the duration in years of each educational level in each country. The data is taken from Cohen and Soto (2007).

A List of Countries in Tables 5 and 7

- **Class 1:** Argentina, Australia, Austria, Belgium, Bulgaria, Canada, China, Costa Rica, Cyprus, Denmark, Fiji, Finland, France, Germany, Greece, Guyana, Hungary, Ireland, Italy, Jamaica, Japan, Korea, Malaysia, Mauritius, Netherlands, New Zealand, Norway, Panama, Romania, Singapore, South Africa, Spain, Sweden, Switzerland, Thailand, Trinidad and Tobago, United Kingdom, United States, Uruguay.
- **Class 2:** Algeria, Angola, Bangladesh, Benin, Bolivia, Brazil, Burkina Faso, Burundi, Cameroon, Central African Republic, Chile, Colombia, Cote d'Ivoire, Dominican Republic, Ecuador, Egypt, El Salvador, Ethiopia, Gabon, Ghana, Guatemala, Haiti, Honduras, India, Indonesia, Iran, Iraq, Jordan, Kenya, Madagascar, Malawi, Mali, Mexico, Morocco, Mozambique, Myanmar, Nepal, Nicaragua, Niger, Nigeria, Paraguay, Peru, Philippines, Portugal, Senegal, Sierra Leone, Sudan, Syria, Tanzania, Tunisia, Turkey, Uganda, Venezuela, Zambia, Zimbabwe.

B List of Countries in Table 6

- **Class 1:** Australia, Austria, Belgium, Canada, China, Denmark, Fiji, Finland, France, Guyana, Hungary, Japan, Korea, Malaysia, Mauritius, Netherlands, New Zealand, Norway, Singapore, Spain, Sweden, Switzerland, United Kingdom, Uruguay.
- **Class 2:** Angola, Argentina, Bangladesh, Bulgaria, Cameroon, Colombia, Costa Rica, Cote d'Ivoire, Cyprus, Dominican Republic, Ecuador, Gabon, Germany, Greece, Guatemala, Honduras, Indonesia, Ireland, Italy, Jamaica, Jordan, Myanmar, Nepal, Nigeria, Panama, Paraguay, Peru, Portugal, Romania, Senegal, South Africa, Thailand, Trinidad and Tobago, Tunisia, Turkey, United States, Venezuela, Zimbabwe.

- **Class 3:** Algeria, Benin, Bolivia, Brazil, Burkina Faso, Burundi, Central African Republic, Chile, Egypt, El Salvador, Ethiopia, Ghana, Haiti, India, Iran, Iraq, Kenya, Madagascar, Malawi, Mali, Mexico, Morocco, Mozambique, Nicaragua, Niger, Philippines, Sierra Leone, Sudan, Syria, Tanzania, Uganda, Zambia.

C Descriptive Statistics for Countries in Tables 5 and 7

Table 8: Years of Educational Attainment by Levels for Class 1 Countries

	No. of Obs.	Mean	Stand.Dev.	Min	Max
Primary education (15+)	156	2.334278	1.083744	0.318334	5.50228
Secondary education (15+)	156	4.272049	2.285101	0.258205	9.431778
Tertiary education (15+)	156	1.139072	0.9897321	0	5.081615
Total years of education (15+)	156	7.745399	2.357525	2.321623	12.32269
Primary education (25+)	156	2.54592	1.170039	0.3809392	5.425602
Secondary education (25+)	156	3.481304	2.259672	0.1314224	9.100007
Tertiary education (25+)	156	1.258744	1.105146	0	5.588048
Total years of education (25+)	156	7.285968	2.541385	1.978461	12.44395

Table 9: Years of Educational Attainment by Levels for Class 2 Countries

	No. of Obs.	Mean	Stand.Dev.	Min	Max
Primary education (15+)	220	1.400487	0.8908363	0.032743	3.722054
Secondary education (15+)	220	1.17492	1.074249	0.0057603	5.821728
Tertiary education (15+)	220	0.2988546	0.4099925	0	3.202738
Total years of education (15+)	220	2.874261	1.97363	0.0545301	9.069577
Primary education (25+)	220	1.252681	0.8860209	0.0293006	3.882302
Secondary education (25+)	220	0.7671715	0.7900454	0	4.764664
Tertiary education (25+)	220	0.3416912	0.4874161	0	4.221591
Total years of education (25+)	220	2.361544	1.783505	0.0523398	8.424913

D Descriptive Statistics for Countries in Table 6

Table 10: Years of Educational Attainment by Levels for Class 1 Countries

	No. of Obs.	Mean	Stand.Dev.	Min	Max
Primary education (15+)	96	2.155932	1.064551	0.318334	4.731682
Secondary education (15+)	96	4.726842	2.337	0.258205	9.431778
Tertiary education (15+)	96	1.268079	1.009797	0.0641069	5.081615
Total years of education (15+)	96	8.150853	2.402838	2.321623	12.32269
Primary education (25+)	96	2.414116	1.167494	0.3809392	5.261272
Secondary education (25+)	96	3.841493	2.39178	0.1314224	9.100007
Tertiary education (25+)	96	1.403274	1.125305	0.0855791	5.588048
Total years of education (25+)	96	7.658884	2.668446	1.978461	12.44395

Table 11: Years of Educational Attainment by Levels for Class 2 Countries

	No. of Obs.	Mean	Stand.Dev.	Min	Max
Primary education (15+)	152	1.985473	1.058444	0.0348266	5.50228
Secondary education (15+)	152	2.206529	1.834738	0.0219743	9.16422
Tertiary education (15+)	152	0.6121178	0.7483985	0	4.737205
Total years of education (15+)	152	4.80412	2.744041	0.1120054	12.25059
Primary education (25+)	152	1.94551	1.167292	0.0323371	5.425602
Secondary education (25+)	152	1.680353	1.64507	0.0130539	8.727866
Tertiary education (25+)	152	0.6847209	0.8528265	0	5.207569
Total years of education (25+)	152	4.310584	2.745485	0.1113263	12.30352

Table 12: Years of Educational Attainment by Levels for Class 3 Countries

	No. of Obs.	Mean	Stand.Dev.	Min	Max
Primary education (15+)	128	1.277291	0.9148768	0.032743	3.722054
Secondary education (15+)	128	1.060568	1.110913	0.0057603	5.821728
Tertiary education (15+)	128	0.223951	0.3011026	0	1.400801
Total years of education (15+)	128	2.561809	1.942351	0.0545301	8.90608
Primary education (25+)	128	1.135005	0.9116557	0.0293006	3.882302
Secondary education (25+)	128	0.6848759	0.8430163	0	4.764664
Tertiary education (25+)	128	0.2558142	0.3481071	0	1.583966
Total years of education (25+)	128	2.075695	1.739408	0.0523398	8.424913

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