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An essay on the contribution of human capital to economic growth

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1. Introduction

The growth effect of human capital is of great interest to both policymakers and economists. The endogenous growth literature, pioneered by the analyses of Lucas (1988) and Romer (1990), stresses the importance of human capital and its connection to economic growth. In particular, more skilled people contribute to knowledge creation and adoption of new technologies and production processes, and thus promote growth. Later on, a neoclassical revival came from Mankiw *et al*. (1992), who developed an augmented Solow model in which education increases the human capital of the labor force. This in turn increases labor productivity, and thus transitional growth towards a higher equilibrium output level. The benefits of education are multifaceted and well-documented in the literature, including social gains (e.g. active citizenship, income distribution, reduced crime rates), and improvements over life expectancy, child mortality, fertility (Breierova and Duflo, 2004) and productivity in general. However, in contrast with common perceptions that view human capital as a key determinant of growth, there is still no consensus regarding the growth effect of human capital. Several explanations have been suggested, including the way human capital is measured in terms of quantity or quality (Barro, 2001; Hanushek and Woessmann, 2008), the quality and reliability of the education data (Krueger and Lindahl, 2001; De la Fuente and Doménech, 2006; Cohen and Soto, 2007; Portela *et al*., 2010), the correct specification of human capital in growth regressions (Krueger and Lindahl, 2001), or even the presence of outliers (Temple, 1999). All of this aside, simply providing for more or higher quality education may not produce the desired outcomes in terms of growth without the appropriate institutions capable of supporting and promoting growth.[1] In other words, schooling is not in itself a sufficient engine of growth (Pritchett, 2001).

Early contributions employed literacy rates and school enrollment ratios as a measure of educational attainment. In fact, (primary) enrollment rates were often used to derive literacy rates. The idea was simple and straightforward: if, for example, 50% of the population were enrolled, this would translate to 50% of the population being literate. However, this conversion of enrollment ratios into equivalent literacy rates is at best inaccurate. This is because an individual without formal schooling may be able to read and write a simple statement, whereas one with formal schooling may remain illiterate. Besides, the concept of literacy is somewhat arbitrary as it is not based on a consistent and objective criterion (Barro, 1991). Enrollment rates, on the other hand, are a satisfying measure of a country's steady state human capital stock only if they are constant over time across countries. This assumption, however, is rejected due to the significant expansion of schooling in developing countries (Pritchett, 2001; Barro and Lee, 2013; Hanushek, 2013; Lee and Lee, 2016). In general, cross-sectional studies tend to find a strong positive association between quantitative measures of human capital and growth. Romer (1989) studies 112 countries over the period 1960-1985 and observes that literacy affects growth in a positive way. Barro (1991) shows that primary

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[1] This actually provides a reasonable explanation as to why underdeveloped countries have failed to experience increased growth rates, despite the significant gains in enrollment especially over the last 50 years. First, a lot of effort was devoted in providing access to schooling, but not much attention was put into ensuring its quality. Second, even if we assume that schooling is of high quality, underdeveloped countries simply lack the desired institutional features (e.g. trade openness) that would allow them to harness the beneficial effects of education.

and secondary enrollment rates are positively connected to growth in 98 countries for the same time period. In contrast with Romer's results, Barro finds that literacy is negatively related to growth. When the enrollment variables are omitted, however, the literacy estimate turns positive and significant. In their seminal paper, Mankiw *et al*. (1992) rely on secondary enrollment rates and find a positive nexus between working age population in secondary school and growth. This result is also confirmed by Durlauf and Johnson (1995), but only for intermediate initial income/low initial literacy countries and high initial income countries.

Since the mid-1990s studies have opted for a stock definition of human capital by frequently employing average years of schooling as a proxy for human capital accumulation. Furthermore, with the development of more complete data sets, panel data analysis becomes common at the same time period.[2] Following a growth accounting approach, Benhabib and Spiegel (1994) find no significant effect for years of schooling and literacy rates and suggest an alternative specification instead, with human capital affecting growth through productivity. Islam (1995) reports a negative, albeit insignificant, coefficient for total years of schooling in a panel regression. Pritchett (2001) also finds a negative and insignificant relationship between educational capital growth and GDP per worker growth. On the other hand, Temple (1999) reveals a positive relationship between schooling and economic growth in 1965-1985 for 78 countries. Interestingly, Krueger and Lindahl (2001) point out that as the frequency of changes over which growth rates are calculated increases (e.g. 5-year versus 10 or 20-year changes) there is less evidence of a positive effect of human capital attainment on growth. This is because the use of longer time horizons may deliver more robust estimates of the growth effect of human capital due to the higher signal-to-noise ratio. Using panel data, Barro (1998) finds that estimates of male years of schooling at the secondary and tertiary levels are positively associated with growth, whereas female years of schooling at the secondary and tertiary level are insignificant in 1965-1995. At the primary level both male and female education turn out to be insignificant in explaining growth. These results are also confirmed by Barro and Sala-i-Martin (2004). Moreover, Cohen and Soto (2007) improve upon Barro and Lee's (2001) data set and construct estimates of educational accumulation for a sample of 95 countries observed from 1960 to 2000. They show that years of schooling are positively connected to growth.

Most of the empirical contributions consider the effect of education quantity on growth, but they do not provide an indication of the variations in the cognitive skills of the working age population. Here comes the issue of education quality. Hanushek and Kimko (2000) use data from the IEA (International Association of the Evaluation of Educational Achievement) and the IAEP (International Assessment of Educational Progress) and construct an educational quality measure for the labor force of 31 countries during the period 1960-1990. They find a positive and highly significant effect of the labor force quality variable on growth. Altinok (2007) constructs measures of human capital quality using data from seven different international assessments (TIMMS, PIRLS, PISA, SACMEQ, PASEC, LLCE and MLA). The author's sample

[2] One of the main reasons behind the surge in growth empirics has been the availability of the Summers and Heston (1988,1991) data set.

consists of 120 countries during 1965-2005. Altinok finds a significant positive link between educational quality and growth of per capita GDP. Hanushek and Woessmann (2012) show that cognitive skills (as measured by the average mathematics and science scores) are significantly related to economic growth in 50 countries over the period 1960-2000. The finding is also robust to a wide range of specifications, samples, and measures of cognitive skills. In a recent work, Altinok *et al*. (2018) construct the most comprehensive data set on education quality for 163 economies over 1965-2015. The authors report a positive and significant relationship between educational achievement and economic growth.

All the results mentioned above rely on parametric estimates; that is a unique response coefficient for human capital is assumed. However, a number of empirical contributions has indicated that this assumption is not always valid. Azariadis and Drazen (1990) emphasize the existence of threshold externalities in the accumulation of human capital, which result in multiple locally stable balanced growth paths. Durlauf and Johnson (1995) employ the regression tree methodology and split countries into different subgroups depending on their initial levels of per capita output and literacy rate. They conclude that each subgroup of countries follows a separate law of motion towards the steady state. Liu and Stengos (1999) estimate an additive semiparametric partially linear model and allow the initial level of GDP per capita and the human capital (as measured by the secondary enrollment rate) to comprise the nonlinear components of the model. They provide evidence for a nonlinear growth effect of initial per capita GDP. On the other hand, the growth effect of human capital can be considered to be linear. Kalaitzidakis *et al*. (2001) follow a similar approach and show that there exists a nonlinear relationship between years of schooling and growth. Specifically, male years of schooling affect growth in a positive way at higher levels of educational attainment. Contrarily, female schooling affects growth positively only at low levels of educational attainment and the effect turns negative at higher levels.

The rest of the dissertation is organized as follows. In the next section we outline a parametric framework widely used in empirical research. In section 3 we provide an overview of the data used. Section 4 contains the growth accounting. Section 5 considers the qualitative dimension of human capital. In section 6 we present a general overview of GAMs and proceed with model fitting. Section 7 concludes the dissertation.

2. Framework

Mankiw *et al*. (1992) augment the textbook Solow (1956) model and assume a Cobb-Douglas production function where aggregate output at time *t* is defined as:

$$Y(t) = K(t)^{\alpha} H(t)^{\beta} (A(t)L(t))^{1-\alpha-\beta} \quad (1)$$

where K is physical capital stock, H is human capital stock, L is labor, and A is a technological parameter; α and β [$\alpha, \beta \in (0,1)$ and $\alpha + \beta < 1$] measure the output elasticity with respect to physical and human capital, respectively. Technology and labor are assumed to grow exponentially at constant rates g and n, respectively. Similar to the Solow growth model, a fraction of the output is saved and invested in physical

(s^k) and human (s^h) capital. Moreover, physical and human capital stocks are assumed to depreciate at the same rate δ. Therefore, the two dynamic equations in this model are:

$$\dot{k}(t) = s^k y(t) - (n + g + \delta)k(t) \tag{2a}$$

$$\dot{h}(t) = s^h y(t) - (n + g + \delta)h(t) \tag{2b}$$

where $y = Y/AL$, $k = K/AL$, and $h = H/AL$ denote quantities per unit of effective labor. Noting that the steady state level of output per worker is $y^* = (k^*)^\alpha (h^*)^\beta$, eq. (2a) and (2b) imply that $k(t)$ and $h(t)$ converge to the steady state values k^* and h^*, determined by:

$$k^* = \left(\frac{(s^k)^{1-\beta}(s^h)^\beta}{n+g+\delta}\right)^{\frac{1}{1-\alpha-\beta}} \tag{3a}$$

$$h^* = \left(\frac{(s^k)^{\alpha}(s^h)^{1-\alpha}}{n+g+\delta}\right)^{\frac{1}{1-\alpha-\beta}} \tag{3b}$$

By substituting eq. (3a) and (3b) into the production function (1) and taking logs, the steady state level of per capita income can be expressed as:

$$ln\left({}^{Y}\!/_{L}\right) = lnA_0 + gt + \frac{\alpha}{1-\alpha-\beta} lns^k - \frac{\alpha+\beta}{1-\alpha-\beta}\ln(n + g + \delta) + \frac{\beta}{1-\alpha-\beta} lns^h \tag{4a}$$

Mankiw *et al*. (1992) point out that the steady state level of output per worker can also be expressed in terms of the steady state level of human capital (h^*), rather than s^h. Solving eq. (3b) for s^h and substituting in eq. (4a), gives:

$$ln\left({}^{Y}\!/_{L}\right) = lnA_0 + gt + \frac{\alpha}{1-\alpha} lns^k - \frac{\alpha}{1-\alpha}\ln(n + g + \delta) + \frac{\beta}{1-\alpha} lnh^* \tag{4b}$$

Notice that the coefficients on the saving rates (of physical and human capital) and population growth terms are different in (4a) and (4b). As the authors suggest, choosing between the alternative formulations depends on "… whether the available data on human capital correspond more closely to the rate of accumulation (s^h) or the level of human capital (h)." Studies that use data on the rate of accumulation of human capital (e.g. literacy or enrollment rates) correspond more closely to the model in (4a). On the other hand, contributions that employ measures of the human capital stock (e.g. years of schooling) correspond more closely to the formulation in (4b).

The model also predicts that each country's income per capita converges to its steady state value $lny_t = \theta lny^* + (1 - \theta)lny_0$, where $\theta = (1 - e^{-\lambda_i t})$ and $\lambda_i = (1 - \alpha - \beta)(n + g + \delta)$ is the country-specific rate of convergence towards the steady state. Finally, subtracting lny_0 from both sides and substituting for the steady state level of income per capita, we get the growth of output per worker between period t_0 and $t_0 + T$:

$$\ln\left({}^{Y}\!/_{L}\right)_{t_0+T} - \ln\left({}^{Y}\!/_{L}\right)_{t_0}$$
$$= \theta(\ln A_0 + gT) + \theta\frac{\alpha}{1-\alpha-\beta}\ln s^k - \theta\frac{\alpha+\beta}{1-\alpha-\beta}\ln(n+g+\delta)$$
$$+ \theta\frac{\beta}{1-\alpha-\beta}\ln s^h - \theta\ln\left({}^{Y}\!/_{L}\right)_{t_0} \tag{5a}$$

or in the case of the steady state level of human capital:

$$\ln\left({}^{Y}\!/_{L}\right)_{t_0+T} - \ln\left({}^{Y}\!/_{L}\right)_{t_0}$$
$$= \theta(\ln A_0 + gT) + \theta\frac{\alpha}{1-\alpha}\ln s^k - \theta\frac{\alpha}{1-\alpha}\ln(n+g+\delta)$$
$$+ \theta\frac{\beta}{1-\alpha}\ln h^* - \theta\ln\left({}^{Y}\!/_{L}\right)_{t_0} \tag{5b}$$

3. Data

The basic data set used in this dissertation combines variables from three sources. The first is version 2.2 (June, 2018) of the Barro-Lee data set, which we use for educational attainment, disaggregated by education level and gender. These data were used to calculate the average years of schooling among the population aged 15 and over[3] both as a whole and at the primary, secondary, and tertiary levels. The second is World Bank's *World Development Indicators*, which we use for real GDP per capita, the growth rate of the working age population,[4] and the investment-to-GDP ratio for each decade. The third is version 9.0 of the Penn World Table (Feenstra *et al*., 2015), from which we extract capital stock depreciation rates.[5] Every variable refers to the average value for each decade except for GDP per capita and years of schooling, which are measured at the beginning of each decade. We have complete data for 490 observations from 142 countries at various stages of economic development. However, we restrict the final sample to 467 observations from 134 economies as we follow Mankiw *et al*. (1992) in excluding the countries for which oil production is the dominant industry.[6] So in what follows, we focus on the "non-oil" sample.[7]

In reference to the definition of human capital, we consider multiple measures. The first is the most widely used in the literature, i.e. mean years of schooling for the entire

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[3] We focus our attention on the population aged 15 and over instead of the population aged 25 and over, because we believe it is more representative of the labor force of developing countries.
[4] We measure n as the average growth rate of the working age population, where working age is defined as 15 to 64.
[5] PWT 9.0 has no data available for Cuba's capital stock depreciation rate, so instead a value equal to $1/30$ is used.
[6] We also follow the authors in assuming that $g = 0.02$. As a comparison to Table 1, we perform an OLS regression for the full sample of countries, in order to examine whether there are any differences with respect to the "non-oil" sample (see appendix Table A1). Notice that the results of the growth regressions are remarkably robust to the inclusion of these countries. However, they are excluded in order to ensure that the results in the following sections are not influenced by them.
[7] A detailed list of the economies that both samples consist of is found in appendix.

population (T). Subsequently, we consider differences by gender: average years of schooling for males (M) and females (F), separately. Next, we take into account the level of education: average years of schooling at the primary level (TPR) and at the post primary level (secondary and tertiary combined or TH). We also consider the educational attainment of males and females at the primary level (MPR and FPR, respectively) and at the post primary level (MH and FH, respectively). In what follows, we combine secondary and tertiary level education for a number of reasons: (i) a lot of countries (especially those located in sub-Saharan Africa, South Asia, Latin America and the Caribbean) have near zero or zero values for educational attainment at the tertiary level, (ii) to restrict the number of measures of human capital, and (iii) to draw a distinction between primary education and education that facilitates the absorption of new technologies (post primary).

4. Growth accounting

In common with earlier contributions we employ panel data over four decades: 1970-80, 1980-90, 1990-00 and 2000-10. We estimate the unrestricted version of the model in (5b) as follows:

$$y_{it} = \alpha_0 + \alpha_1 D_t + \alpha_2 D_j + \alpha_3 \ln s_{it}^k + \alpha_4 \ln(n_{it} + g + \delta_{it}) + \alpha_5 \ln x_{it} + \alpha_6 \ln h_{it} + \varepsilon_{it} \quad (6)$$

where y_{it} refers to the growth rate of GDP per capita during each period, x_{it} is per capita GDP at the beginning of each period, and h_{it} is human capital measured as mean years of schooling. D_t and D_j are dummy variables for each decade and for the countries in sub-Saharan Africa or Latin America and the Caribbean, respectively. The need for dummies to identify the time period over which the model is estimated is evident from eq. (5b). Regional dummies have also been included to account for idiosyncratic economic conditions in these two regions (high levels of income inequality in Latin America[8] and high ethnolinguistic fractionalization in Africa[9]).

The parametric estimates of the growth regression are presented in Table 1. While it is not the focus of our analysis, all specifications include GDP per capita in the beginning of each decade, in order to provide consistent evidence on conditional convergence[10] (i.e. countries with lower initial income tend to grow more rapidly). The coefficients for investment and initial GDP per capita are of the anticipated sign, highly significant and are robust to the alternative measures of human capital. The coefficient estimates for the working age population growth, however, are insignificant and not of the anticipated sign. As expected, estimates of the dummy variables for sub-Saharan Africa and Latin America are negative and significant at a 1% level. The dummies for the 1980s and the 1990s are highly significant and negative, while the 1970s dummy is

[8] Despite the major decline in inequality and general improvements (particularly in the distribution of wealth) between 2002 and 2014, Latin America and the Caribbean remains the most unequal region in the world.

[9] It is widely believed that ethnic, linguistic, and religious heterogeneity leads to political instability, poor quality of institutions, badly designed economic policy and disappointing economic performance.

[10] The convergence is conditional in that it predicts higher growth in response to lower initial income only if the other explanatory variables are held constant.

Table 1. OLS regressions: Barro & Lee human capital. Dependent variable: average GDP per capita growth, 1970-2010.

	(1) T	(2) M & F	(3) TPR & TH	(4) MPR & FPR	(5) MH & FH
cons	.120***	.135***	.109***	.128***	.124***
	(7.16)	(7.39)	(6.57)	(6.90)	(7.30)
D_{1970}	.006*	.005	.003	.007**	.003
	(1.67)	(1.36)	(0.79)	(2.04)	(0.87)
D_{1980}	- .014***	- .015***	- .016***	- .014***	- .015***
	(- 5.15)	(- 5.26)	(- 5.54)	(- 5.30)	(- 5.23)
D_{1990}	- .012***	- .012***	- .013***	- .012***	- .013***
	(- 3.94)	(- 4.07)	(- 4.23)	(- 4.12)	(- 4.06)
D_{Africa}	- .013***	- .015***	- .017***	- .014***	- .016***
	(- 3.95)	(- 4.54)	(- 4.90)	(- 4.10)	(- 4.79)
$D_{Lat.Am.}$	- .011***	- .014***	- .013***	- .013***	- .015***
	(- 3.58)	(- 4.29)	(- 4.53)	(- 4.06)	(- 4.49)
ln s^k	.026***	.024***	.025***	.024***	.026***
	(3.79)	(3.50)	(3.66)	(3.47)	(3.80)
ln $(n + g + \delta)$	.011	.010	.009	.011	.008
	(1.56)	(1.36)	(1.35)	(1.54)	(1.10)
ln x	- .004***	- .004***	- .003***	- .004***	- .003**
	(- 2.76)	(- 2.95)	(- 2.62)	(- 3.77)	(- 2.21)
ln (T)	.005*				
	(1.93)				
ln (M)		- .020**			
		(- 2.25)			
ln (F)		.017***			
		(3.00)			
ln (TPR)			.013***		
			(4.62)		
ln (TH)			- .006**		
			(- 2.08)		
ln (MPR)				- .007	
				(- 0.71)	
ln (FPR)				.011*	
				(1.84)	
ln (MH)					- .017***
					(- 3.31)
ln (FH)					.013***
					(3.30)
R^2 (adj.)	0.27	0.28	0.29	0.28	0.28
Observations			467		
Countries			134		

Notes: Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. x = initial GDP per capita, s^k = ratio of investment to GDP, T = total mean years of schooling, TPR & TH = total mean years of schooling at the primary & at the post primary level, M & F = male & female mean years of schooling, MPR & FPR = male & female mean years of schooling at the primary level, MH & FH = male & female mean years of schooling at the post primary level. Countries are listed in the appendix.

positive, but in most cases insignificant. In general, most measures of male human capital show a negative and significant effect, whereas measures of female human capital show a significant positive effect. This finding is in accordance with Kalaitzidakis *et al*. (2001). More specifically, growth is insignificantly related to male schooling at the primary level. In contrast, female schooling at the primary level exerts a positive effect on growth. This probably reflects the social benefits of female basic education, such as reduced early fertility rates and lower infant and maternal mortality rates. The relationship carries over to the secondary and tertiary level as well, which is quite surprising as they contradict most of the existing literature that assigns a positive effect on male post primary schooling and a negative effect on female post primary schooling.[11] We should note, however, that the disaggregated measures of human capital are highly correlated, and thus we discourage blind acceptance of whatever the results suggest. We address the issue of multicollinearity in section 4.2 below.

4.1. Robustness checks

We checked the robustness of the estimates of human capital in Table 1 by performing MM-estimation at the 85% and 95% efficiency levels. This is aimed at analyzing whether the significance of human capital in the previous section is due to the presence of outliers. MM-estimators combine high breakdown point[12] with high efficiency under normality. For computing the estimator, the iteratively reweighted least squares (IRLS) algorithm (see Salibian-Barrera and Yohai, 2006) can be used. The results are presented in Tables 2a and 2b, along with graphical tools to help us identify outliers. The resulting plots are pictured in Figures 1a and 1b. Since several outliers of all types are present, there is a serious risk that the least squares estimator becomes heavily influenced. As can be seen in Table 2a, mean years of schooling for the total population (T) increase in magnitude and become significant at a 1% level. On the other hand, average years of schooling for males (M) and average years of schooling at the post primary level (TH) turn out to be insignificant. Labor force growth turns out to be significant in all specifications and is now of he anticipated sign. The dummy variable for the 1970s becomes significant in almost every case, while the 1990s dummy is flagged as insignificant in all specifications. When the 95% efficiency level is considered (Table 2b), not much is changed with respect to the 85% level. The only noticeable difference is that female mean years of schooling as a whole (F) and at the primary level (FPR) increase in magnitude and become more important in terms of significance. The 1990s dummy also turns out to be significant. In sum, the evidence is consistent with the conclusion that the significant effect of schooling is not driven by outliers, as the coefficients for schooling remain quite stable.

[11] It is worth noting that the results do not change when school attainment is measured as the average value for each decade, rather than at the beginning of each decade.
[12] The breakdown point of an estimator refers to the proportion of outliers that can be addressed before these observations affect the model, and it is one of the most popular measures of robustness.

Table 2a. MM – regressions (85% efficiency): Barro & Lee human capital. Dependent variable: average GDP per capita growth, 1970-2010.

	(1) T	(2) M & F	(3) TPR & TH	(4) MPR & FPR	(5) MH & FH
cons	.086*** (5.93)	.097*** (5.98)	.087*** (5.67)	.095*** (5.81)	.097*** (6.27)
D_{1970}	.006** (2.22)	.005** (2.02)	.004 (1.54)	.004* (1.89)	.005* (1.75)
D_{1980}	- .008*** (- 2.78)	- .008*** (- 2.81)	- .009*** (- 2.93)	- .008*** (- 3.03)	- .008*** (- 2.69)
D_{1990}	- .003 (- 1.15)	- .003 (- 1.17)	- .003 (- 1.37)	- .003 (- 1.34)	- .002 (- 1.07)
D_{Africa}	- .012*** (- 4.34)	- .013*** (- 4.63)	- .013*** (- 4.43)	- .014*** (- 4.72)	- .012*** (- 4.40)
$D_{Lat.Am.}$	- .007*** (- 2.85)	- .011*** (- 3.06)	- .008*** (- 3.09)	- .010*** (- 3.23)	- .012*** (- 3.20)
ln s^k	.031*** (6.58)	.028*** (5.75)	.030*** (6.40)	.029*** (5.92)	.030*** (6.23)
ln $(n+g+\delta)$	- .009* (- 1.74)	- .010* (- 1.86)	- .009* (- 1.71)	- .010* (- 1.80)	- .011** (- 2.15)
ln x	- .006*** (- 6.11)	- .006*** (- 6.39)	- .006*** (- 5.71)	- .006*** (- 6.34)	- .006*** (- 5.76)
ln (T)	.008*** (3.35)				
ln (M)		- .010 (- 1.15)			
ln (F)		.013** (2.18)			
ln (TPR)			.009*** (3.26)		
ln (TH)			- .0004 (- 0.17)		
ln (MPR)				- .006 (- 0.72)	
ln (FPR)				.010* (1.84)	
ln (MH)					- .013** (- 2.30)
ln (FH)					.013*** (2.97)
R^2 (adj.)	0.40	0.40	0.40	0.40	0.39
Observations			467		
Countries			134		

Notes: Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. x = initial GDP per capita, s^k = ratio of investment to GDP, T = total mean years of schooling, TPR & TH = total mean years of schooling at the primary & at the post primary level, M & F = male & female mean years of schooling, MPR & FPR = male & female mean years of schooling at the primary level, MH & FH = male & female mean years of schooling at the post primary level. Countries are listed in the appendix.

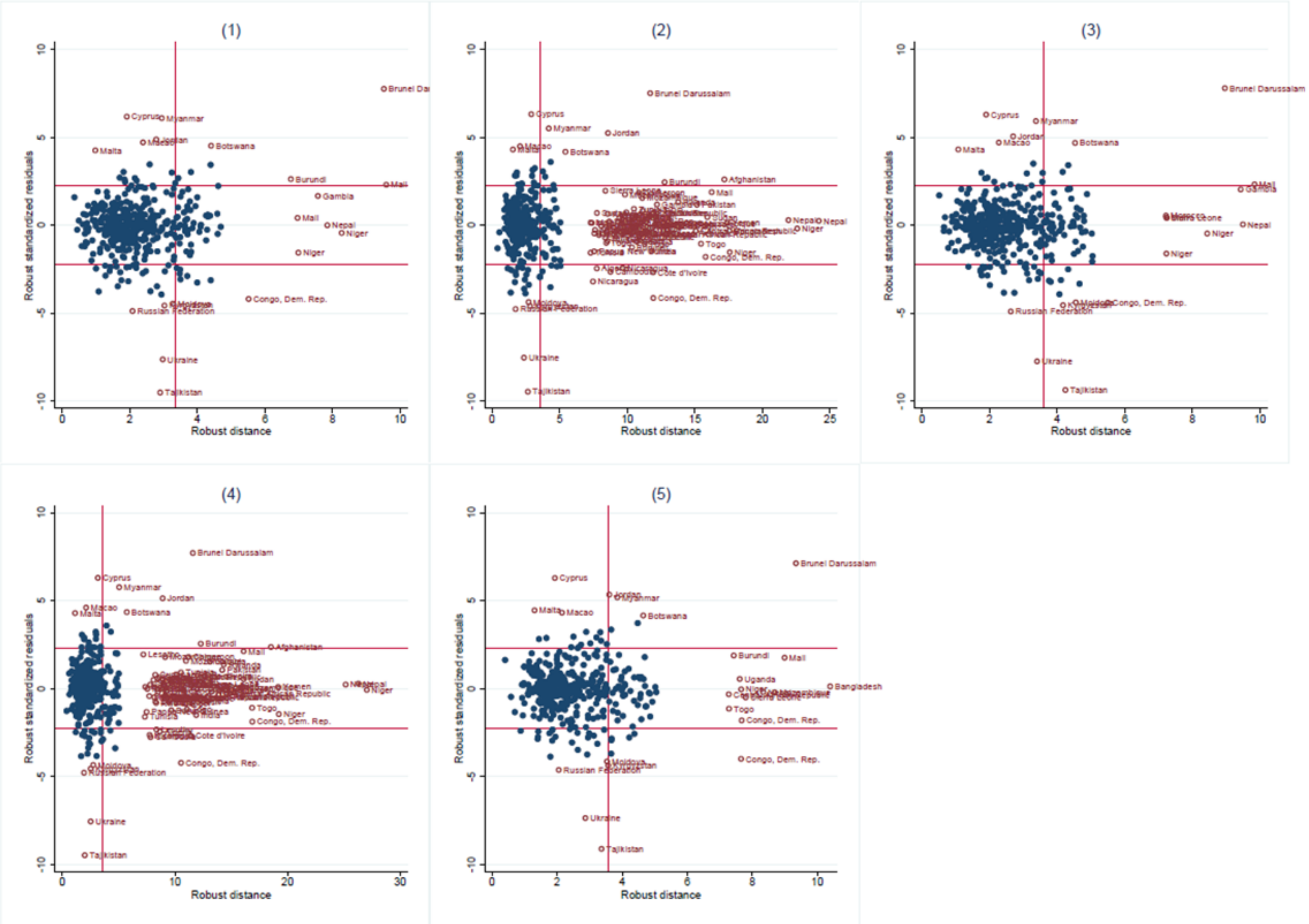

Figure 1a. Diagnostic plots of robust standardized residuals versus roust Mahalanobis distances (85% efficiency).

Table 2b. MM – regressions (95% efficiency): Barro & Lee human capital. Dependent variable: average GDP per capita growth, 1970-2010.

	(1) T	(2) M & F	(3) TPR & TH	(4) MPR & FPR	(5) MH & FH
cons	.089***	.029***	.090***	.099***	.101***
	(6.68)	(6.38)	(6.49)	(6.61)	(7.12)
D_{1970}	.006**	.005**	.004	.004*	.005*
	(2.25)	(2.00)	(1.54)	(1.90)	(1.75)
D_{1980}	- .010***	- .010***	- .010***	- .010***	- .010***
	(- 3.75)	(- 3.78)	(- 3.93)	(- 4.09)	(- 3.57)
D_{1990}	- .004*	- .004*	- .005**	- .004**	- .004*
	(- 1.76)	(- 1.80)	(- 1.99)	(- 1.98)	(- 1.70)
D_{Africa}	- .012***	- .013***	- .013***	- .014***	- .012***
	(- 4.59)	(- 4.94)	(- 4.71)	(- 5.02)	(- 4.63)
$D_{Lat.Am.}$	- .009***	- .012***	- .010***	- .011***	- .012***
	(- 3.42)	(- 3.81)	(- 3.64)	(- 3.90)	(- 3.95)
ln s^k	.030***	.028***	.030***	.029***	.030***
	(7.06)	(6.20)	(6.92)	(6.47)	(6.87)
ln $(n + g + \delta)$	- .008	- .009*	- .008	- .009	- .010**
	(- 1.55)	(- 1.72)	(- 1.48)	(- 1.63)	(- 2.00)
ln x	- .006***	- .006***	- .006***	- .006***	- .006***
	(- 6.19)	(- 6.50)	(- 5.57)	(- 6.64)	(- 5.77)
ln (T)	.008***				
	(3.48)				
ln (M)		- .012			
		(- 1.46)			
ln (F)		.014***			
		(2.66)			
ln (TPR)			.009***		
			(3.46)		
ln (TH)			- .0005		
			(- 0.22)		
ln (MPR)				- .008	
				(- 1.03)	
ln (FPR)				.012**	
				(2.27)	
ln (MH)					- .013***
					(- 2.70)
ln (FH)					.013***
					(3.44)
R^2 (adj.)	0.38	0.39	0.38	0.39	0.39
Observations			467		
Countries			134		

Notes: Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. x = initial GDP per capita, s^k = ratio of investment to GDP, T = total mean years of schooling, TPR & TH = total mean years of schooling at the primary & at the post primary level, M & F = male & female mean years of schooling, MPR & FPR = male & female mean years of schooling at the primary level, MH & FH = male & female mean years of schooling at the post primary level. Countries are listed in the appendix.

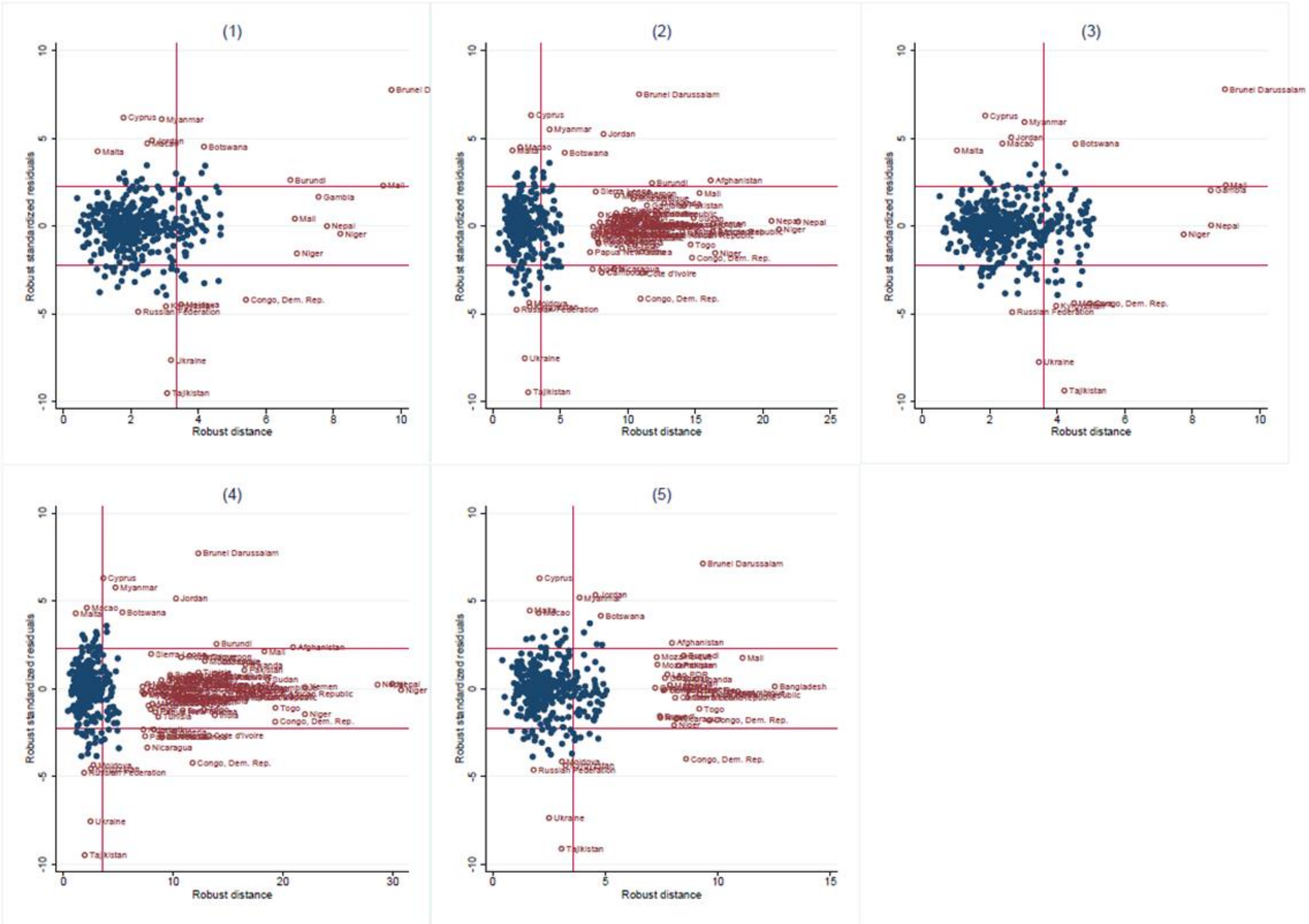

Figure 1b. Diagnostic plots of robust standardized residuals versus roust Mahalanobis distances (95% efficiency).

4.2. Dealing with multicollinearity

Following the usual notation, the linear regression model can be written in matrix form as:

$$y = X\beta + \varepsilon$$

where y is the $n \times 1$ response vector, X is the $n \times p$ matrix of predictors, β is a $p \times 1$ vector of unknown parameters, and ε a $n \times 1$ vector of the underlying errors. As we do not know the true parameters, we have to estimate them from the sample. In the Ordinary Least Squares (OLS) approach, we estimate them as $\hat{\beta}$ in such a way, that the sum of squared residuals is as small as possible. In other words, we minimize the following loss function:

$$\sum_{i-1}^{n}(y_i - x_i'\beta)^2 = |y - X\beta|^2$$

OLS regression uses the following formula to estimate coefficients:

$$\hat{\beta}_{\mathrm{OLS}} = (X'X)^{-1}X'y$$

The OLS estimator has the desired property of being unbiased. When multicollinearity is present, however, least squares estimates are still unbiased, but their variances are large so they may be far from the true value. As it is evident in Table 3 the correlations between male and female human capital variables are near perfect. Looking at correlations only among pairs of predictors, however, is limiting. It is possible that the pairwise correlations are small, and yet a linear dependence exists among three or even more variables. That is why many regression analysts often rely on variance inflation factors (VIF) to help detect multicollinearity. A VIF of 10 or more for large data sets indicates a multicollinearity problem, while for small datasets, even VIF values of 5 or more can signify multicollinearity. Table 4 presents the VIF values. Since all male and female human capital variables have VIF values greater than 10, multicollinearity is indeed a problem in our sample. Surprisingly, average years of schooling at the primary and at the post primary level have VIFs lower than 5, despite being highly correlated. One approach to deal with multicollinearity is to use an estimator which is no longer unbiased, but has considerably less variance than the least squares estimator. This approach is called regularization and is almost always beneficial for the predictive performance of the model. There are two types of regularization. The first type of regularization, ℓ_1 regularization, limits the size of the coefficients by adding a penalty on the absolute values of the coefficients. This sometimes results in the elimination of some coefficients altogether, which can yield sparse models. The other type of regularization, ℓ_2 regularization, adds a quadratic penalty term on the sum of squares of the coefficients. All coefficients are shrunk by the same factor, so none are eliminated. Thus, unlike ℓ_1 regularization, ℓ_2 will not result in sparse models.

Table 3. Correlation matrix of predictors.

	ln x	ln (T)	ln (M)	ln (F)	ln (TPR)	ln (TH)	ln (MPR)	ln (MH)	ln (FPR)	ln (FH)	ln s^k	ln $(n+g+\delta)$
ln x	1											
ln (T)	0.7051	1										
ln (M)	0.6927	0.9900	1									
ln (F)	0.6961	0.9886	0.9604	1								
ln (TPR)	0.6669	0.9687	0.9495	0.9706	1							
ln (TH)	0.6963	0.9192	0.9250	0.8874	0.8040	1						
ln (MPR)	0.6421	0.9529	0.9527	0.9375	0.9882	0.7865	1					
ln (MH)	0.6760	0.8911	0.9123	0.8467	0.7659	0.9913	0.7596	1				
ln (FPR)	0.6624	0.9588	0.9238	0.9812	0.9884	0.7951	0.9573	0.7488	1			
ln (FH)	0.7071	0.9412	0.9289	0.9291	0.8458	0.9867	0.8150	0.9601	0.8498	1		
ln s^k	0.3208	0.3775	0.3620	0.3883	0.3670	0.3443	0.3451	0.3326	0.3781	0.3633	1	
ln $(n+g+\delta)$	-0.2919	-0.3514	-0.3665	-0.3213	-0.2931	-0.3814	-0.2940	-0.3894	-0.2755	-0.3550	0.0246	1

Notes: x = initial GDP per capita, s^k = ratio of investment to GDP, T = total mean years of schooling, TPR & TH = total mean years of schooling at the primary & at the post primary level, M & F = male & female mean years of schooling, MPR & FPR = male & female mean years of schooling at the primary level, MH & FH = male & female mean years of schooling at the post primary level.

Table 4. Variance Inflation Factor (VIF) values. Barro & Lee human capital. Dependent variable: average GDP per capita growth.

	(1) T	(2) M & F	(3) TPR & TH	(4) MPR & FPR	(5) MH & FH
ln s^k	1.35	1.39	1.35	1.39	1.34
ln x	2.31	2.30	2.40	2.16	2.32
ln (T)	3.22				
ln (M)		17.33			
ln (F)		17.05			
ln (TPR)			4.90		
ln (TH)			3.48		
ln (MPR)				13.62	
ln (FPR)				14.83	
ln (MH)					16.76
ln (FH)					18.71

Notes: x = initial GDP per capita, s^k = ratio of investment to GDP, T = total mean years of schooling, TPR & TH = total mean years of schooling at the primary & at the post primary level, M & F = male & female mean years of schooling, MPR & FPR = male & female mean years of schooling at the primary level, MH & FH = male & female mean years of schooling at the post primary level.

Ridge regression, also known as "Tikhonov regularization," belongs to a class of regression tools that use ℓ_2 regularization, while the lasso (least absolute shrinkage and selection operator) utilizes the ℓ_1 regularization technique. Both regressions have a shrinkage parameter that needs to be specified, typically by cross-validation. In ridge regression the OLS loss function is augmented in such a way that we not only minimize the sum of squared residuals, but also penalize the size of parameter estimates, in order to shrink them towards zero:

$$\frac{1}{n}\sum_{i-1}^{n}(y_i - x_i'\beta)^2 + \frac{\lambda}{n}\sum_{j=1}^{p}\psi_j^2\beta_j^2$$

where λ is a tuning parameter and ψ_j are predictor-specific penalty loadings. Solving this for β gives the ridge regression estimates:

$$\hat{\beta}_{\text{ridge}} = (X'X + \lambda\Psi'\Psi)^{-1}X'y$$

where Ψ is a diagonal matrix of penalty loadings. So, ridge regression essentially adds positive constants to the cross-product matrix, forming a new matrix denoted by $(X'X + \lambda\Psi'\Psi)$. The matrix we now need to invert no longer has a determinant near zero, so the solution does not lead to large variance in the estimated parameters. The new estimates are no longer unbiased, since their expected values are not equal to the true values. Generally, they tend to underestimate the true values. The variance of this new estimate, however, can be so much lower than that of the least squares estimator, that the total expected mean squared error is also less. The tuning parameter controls the degree of penalization. When $\lambda = 0$, ridge regression is equal to least squares regression ($\hat{\beta}_{\text{ridge}} = \hat{\beta}_{\text{OLS}}$). If $\lambda = \infty$, all coefficients are shrunk to zero ($\hat{\beta}_{\text{ridge}} = 0$). The ideal penalty is therefore somewhere in between 0 and ∞. There are two ways for choosing the value of λ. A more traditional approach would be to choose λ such that some information criterion is minimized. An alternative approach is to perform cross-validation and select the value of λ that minimizes the cross-validated sum of squared residuals (or some other measure). The former approach emphasizes the model's fit to the data, while the latter is more focused on its predictive performance.[13] It is important to note that all ridge regression calculations are based on standardized variables. When the final regression coefficients are displayed, they are adjusted back into their original scale.

On the other hand, the lasso minimizes the mean squared error subject to a penalty on the absolute size of coefficient estimates:

$$\hat{\beta}_{\text{lasso}} = \arg\min_{\beta} \frac{1}{n}\sum_{i=1}^{n}(y_i - x_i'\beta)^2 + \frac{\lambda}{n}\sum_{j=1}^{p}\psi_j\left|\beta_j\right|$$

However, the lasso approach has received a lot of criticism, as its variable selection process can be too dependent on data and therefore unstable. Specifically, in situations where there is a group of highly correlated variables, the lasso tends to select one variable from the group and ignore the others. In addition, in small-*n*-large-*p* datasets lasso selects at most *n* variables before it saturates.[14] To overcome these limitations, Zou and Hastie (2005) introduced the elastic net regression, which combines the penalties of ridge regression and lasso to get the best of both worlds:

$$\hat{\beta}_{\text{en}} = \arg\min_{\beta} \frac{1}{n}\sum_{i=1}^{n}(y_i - x_i'\beta)^2 + \alpha\frac{\lambda}{n}\sum_{j=1}^{p}\psi_j\left|\beta_j\right| + (1-\alpha)\frac{\lambda}{n}\sum_{j=1}^{p}\psi_j^2\beta_j^2$$

The elastic net parameter α determines the relative contribution of ℓ_1 (lasso-type) to ℓ_2 (ridge-type) penalization. When $\alpha = 0$, the elastic net becomes ridge regression, whereas for $\alpha = 1$ the elastic net is equivalent to the lasso. In our study, we first estimated an elastic net regression using cross-validation to compute the optimal α value.[15] A value of α equal to zero is optimal in a mean square error sense, so in what follows we focus on ridge regression. This is actually reasonable, since for typical situations where the number of observations is larger than the number of predictors, if there are high correlations between predictors, it has been empirically observed that the predictive performance of the lasso is dominated by ridge regression (Tibshirani, 1996).

The results of the analysis are presented below. On the *x*-axis the different values of λ are shown. Each line represents one of the explanatory variables and its role in the model. Looking at Figure 2 it is clear that the most influential variable across all specifications is investment as it steadily and positively affects GDP per capita growth. Regarding the human capital measures an interesting pattern emerges, which is in line with our previous findings. The effect of male and female educational variables on growth appears to be of the same size, but of the opposite sign. Specifically, male

[13] Choosing a value for λ is not a simple task and is perhaps one major reason why ridge regression is not used as much, despite its popularity.
[14] For a detailed discussion of the lasso and its limitations, see Tibshirani (1996).
[15] A total of 500 alpha values were used for cross-validation.

Table 5. Ridge regressions: Barro & Lee human capital. Dependent variable: average GDP per capita growth, 1970-2010.

	(1) T $\lambda = 148.79$†	(2) M & F $\lambda = 102.56$†	(3) TPR & TH $\lambda = 93.45$†	(4) MPR & FPR $\lambda = 135.57$†	(5) MH & FH $\lambda = 23.15$†
D_{1970}	.006	.006	.005	.007	.003
D_{1980}	- .011	- .012	- .013	- .011	- .015
D_{1990}	- .010	- .010	- .011	- .010	- .012
D_{Africa}	- .010	- .011	- .013	- .011	- .015
$D_{Lat.Am.}$	- .008	- .010	- .010	- .009	- .012
ln s^k	.023	.024	.024	.022	.026
ln $(n + g + \delta)$	.009	.009	.009	.009	.008
ln x	- .002	- .003	- .003	- .003	- .003
ln (T)	.004				
ln (M)		- .002			
ln (F)		.005			
ln (TPR)			.009		
ln (TH)			- .003		
ln (MPR)				.002	
ln (FPR)				.004	
ln (MH)					- .009
ln (FH)					.007
			Partialled – out		
cons	.099	.107	.100	.102	.118
Observations			467		
Countries			134		

Notes: x = initial GDP per capita, s^k = ratio of investment to GDP, T = total mean years of schooling, TPR & TH = total mean years of schooling at the primary & at the post primary level, M & F = male & female mean years of schooling, MPR & FPR = male & female mean years of schooling at the primary level, MH & FH = male & female mean years of schooling at the post primary level. λ controls the overall degree of penalization. Countries are listed in the appendix.
†Selected by the *Extended Bayesian Information Criterion (EBIC)*.

education variables affect growth in a negative way, while female education variables affect growth positively. The dummy variables for sub-Saharan Africa and Latin America, as well as those for the 1980s and 1990s affect growth negatively. In contrast, average years of schooling at the primary level, labor force growth, and the dummy variable for the 1970s have a positive impact on growth. Initial GDP per capita and average years of schooling at the post primary level seem to be less significant in explaining growth.

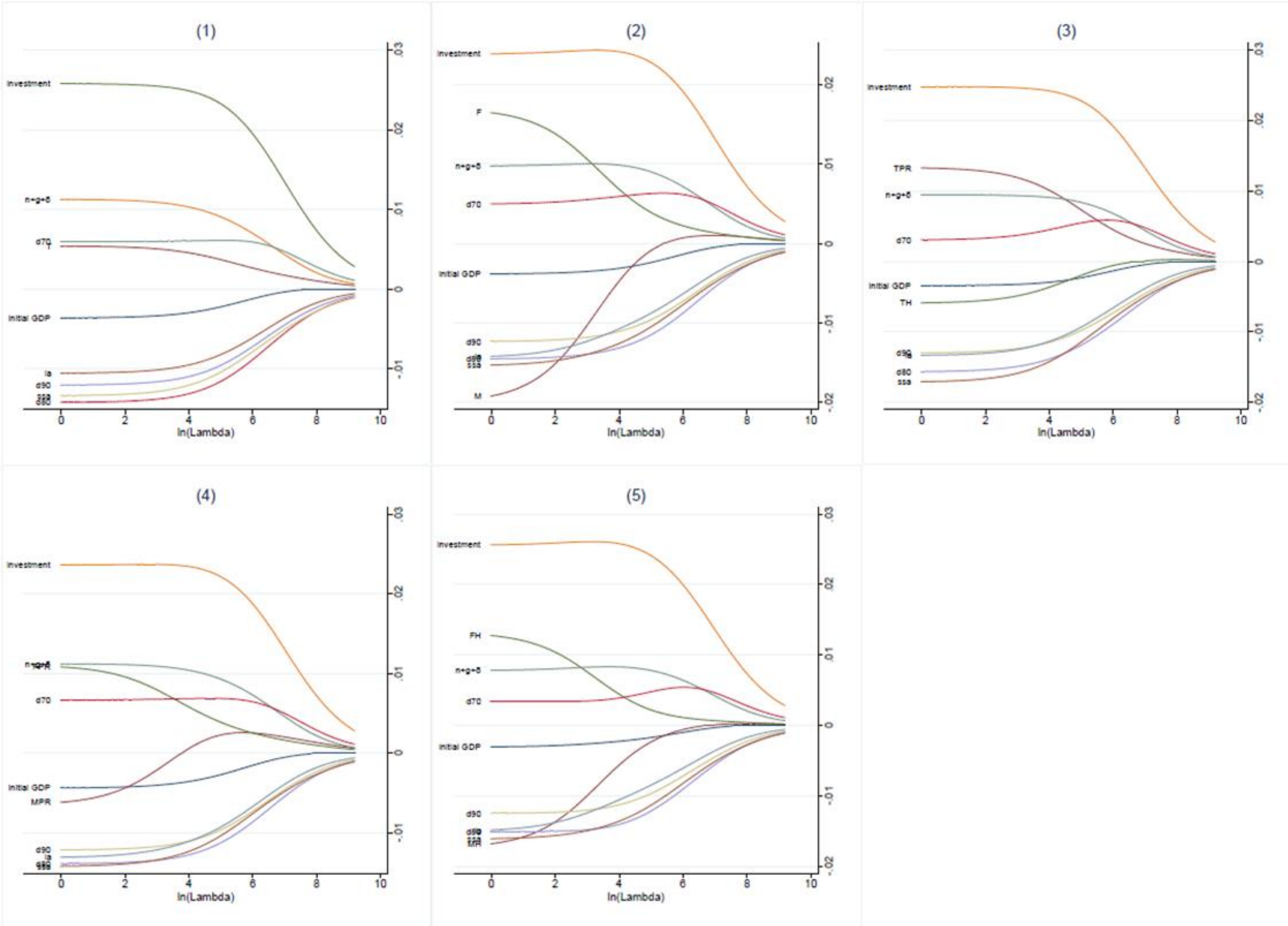

Figure 2. Plots of the coefficient estimates against ln λ.

5. Quality of human capital

An issue that has received considerable attention in the literature as a potential reason for the weak effect of human capital on growth is the focus on quantitative measures, such as average years of schooling. These measures have two very important drawbacks: (i) they implicitly assume that a year of schooling in, say, Niger or Mozambique has the same quality as a year of schooling in Finland or Japan, and (ii) they completely disregard the role of non-school factors (e.g. family, peers) in effectively raising cognitive skills. Several authors have suggested to account for the quality of human capital in terms of the existing stock of knowledge in the population by using measures based on teaching inputs or output measures like scores on internationally comparable assessments. The use of input-based measures of human capital quality has been extensive in the literature to investigate student quality and its determinants, but overall the results have been mixed as to whether the pupil-teacher ratio or related measures of expenditures on education have an impact on the quality of human capital and growth. For instance, Barro (1991) finds a negative relationship between the pupil-teacher ratio for primary schools and per capita growth, while for secondary schools the ratio is insignificant in explaining growth. Furthermore, Kalaitzidakis *et al*. (2001) show that for low values of government expenditures on education the effect on growth is insignificant.

Ideally, measures of cognitive skills of the working age population would be more suitable and informative for the underlying question, but unfortunately no such measures exist, at least on an extensive scale.[16] In order to investigate the effect of applying qualitative measures of human capital rather than quantitative, we therefore conducted the same analysis using the Programme for International Student Assessment (PISA) scores as an output-based measure for the quality of human capital.[17] PISA is an international survey carried out by the OECD in member and non-member countries intended to evaluate 15-year-old students' performance in mathematics, science, and reading. The first PISA study was performed in 2000 and is repeated every three years ever since. To allow for meaningful comparisons the PISA results are standardized, so that the OECD average in each subject is 500 and the standard deviation is 100. Regrettably, the coverage of PISA is rather limiting as its participants are primarily OECD-member countries, though with each cycle more non-member countries are included in the assessment. It is also important to note that in some cases (most notably in Argentina, Azerbaijan, China, and India) the reported scores are only from selected

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[16] To the best of our knowledge only three studies of this type exist: the IALS (International Adult Literacy Survey), the Adult Literacy and Life skills (ALL) Survey, and the PIAAC (Programme for the International Assessment of Adult Competencies). The first assessment, which was carried out between 1994 and 1998 at two-year intervals, provided information on the literacy skills of adults (16-65 years old) for 22 countries, while the second was conducted in 11 countries between 2003 and 2008. The third assessment, PIAAC, is conducted by the OECD and is the most comprehensive data set for the skills of the working age population. In the most recent study (2017), a total of 38 countries participated. Unfortunately, the aforementioned surveys are rather limiting, and thus not suitable for our analysis.

[17] The advantage of PISA over other assessments lies in the fact that it is an age-based rather than a grade-based survey. Since school duration varies across countries, it is clear that age forms a more consistent and objective criterion for student assessment. For example, 8th graders in the US are typically 13-14 years old, while in some European countries they may be 12-13 or even 14-15 years old.

regions/provinces within the country, and therefore not representative of the entire country's human capital quality.

Before we proceed any further into this section, it is imperative that we draw a distinction which is not often encountered in the literature. When researchers employ measures of cognitive skills, such as scores on international assessments, to proxy human capital quality, they tend to make inferences about the educational policies and practices that are implemented in different countries, based on the resulting estimates. This, however, is erroneous as cognitive skills emphasize total outcomes of education, and thus incorporate skills from different sources (e.g. family, school, private tutoring, innate ability). Therefore, it should be stressed that when we make use of the term "quality of human capital" we refer to the quality of human capital in a general sense, not the quality of schooling.

Figure 3 plots the average growth in real GDP per capita between 2000 and 2015 against the average of all standardized test scores for each country. The five top performing economies are, not surprisingly, China,[18] Singapore, Hong Kong, South Korea, and Finland. The strength of education in East Asia is well documented in the literature, as the aforementioned countries rank consistently among the top five in mathematics and the sciences.[19] On the other hand, the countries which rank the lowest are Kyrgyzstan, the Dominican Republic, Kosovo, Algeria, and Peru. Another conclusion that can be drawn from this graphical analysis is that students in high income countries do not necessarily perform better. For instance, Vietnam ranks considerably higher on the PISA scale than the United States, Luxembourg, and other OECD countries. Figure 4 shows the average performance of males and females over the 2000-2015 period for each subject. It is interesting to note that females achieved higher scores on the reading scale in every country (Fig. 4a), while in mathematics the picture is contrasting as males tend to outperform females in most countries (Fig. 4b). Finally, on the science scale the results are mixed as males and females achieve higher scores in 39 and 38 countries, respectively (Fig. 4c).

5.1. *Cognitive skills and growth*

The growth model in eq. (6) is estimated for the 76 countries[20] with cognitive skills and economic data over the period 2000-2015. The sub-Saharan Africa dummy is replaced by an East Asia dummy, because (i) no country from the sub-Saharan Africa region has ever participated in the assessment, and (ii) East Asian countries exhibit remarkably high levels of student achievement. The data for each country's PISA performance come from the *World Bank EdStats*. Table 6 presents the results for the three subjects in which students are assessed. The test scores, which are also subdivided by gender, are not given for a particular year, but instead are the simple average of the standardized mathematics, science, and reading scores each country achieved. Columns

[18] Represented by the Beijing, Shanghai, Jiangsu, and Guangdong provinces.
[19] In fact, Singapore was the top performing country across all academic subjects in the latest PISA report (2015).
[20] Liechtenstein is excluded due to lack of economic data.

Table 6. Cross-country growth regressions: PISA test scores. Dependent variable: average GDP per capita growth, 2000-2015.

	(1) Math	(2) Math males & females	(3) Science	(4) Science males & females	(5) Reading	(6) Reading males & females
ln x	- .017*** (- 6.04)	- .016*** (- 6.07)	- .014*** (- 5.54)	- .014*** (- 5.57)	- .014*** (- 5.44)	- .014*** (- 5.61)
Math	.0002*** (4.41)					
Math males		- .0002 (- 1.50)				
Math females		.0005*** (2.82)				
Science			.0001** (2.43)			
Science males				.0001 (0.32)		
Science females				.0001 (0.20)		
Reading					.0001** (2.33)	
Reading males						.0001 (0.64)
Reading females						- .00001 (- 0.04)
R^2 (adj.)	0.63	0.64	0.54	0.54	0.54	0.54
Countries				76		

Notes: Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Regressions include regional dummies, additional controls for the ratio of investment to GDP and population growth, and a constant. x = initial GDP per capita. Math, Science, and Reading = PISA performance on the mathematics, science, and reading scale, respectively. Each variable refers to the average value for the period 2000-2015, except for initial GDP per capita which is measured in 2000. Countries are listed in the appendix.

1, 3, and 5 suggest that if the average performance in each subject increases by 100 points (i.e. by one standard deviation of the average student in an OECD country), growth of per capita GDP will increase by approximately 1.3% to 2%. Of course, it seems unlikely that any country will experience an improvement of this size in its average performance over any reasonable time period. On the other hand, even a more reasonable increase of, say, 25 points is associated with approximately 0.3% to 0.5% higher growth. When we subdivide scores by gender (col. 2, 4, and 6) almost all measures are insignificant, with the exception of female performance in mathematics. This is probably due to the near perfect correlation of male and female measures of human capital quality, so these coefficient estimates are not very reliable.

Since the majority of the international assessments have focused on mathematics and science, for it is easier to identify a common set of expected skills, our focus also turns to these subjects for the remainder of this section. Table 7 considers different samples in order to examine whether the significance of human capital quality is driven by specific subgroups of countries. When the full sample is considered (col. 1), human capital quality has a strong positive impact on growth. In particular, a 10-point increase in a country's average PISA performance is associated with 0.2% higher growth.

Table 7. Cross-country growth regressions: PISA test scores. Dependent variable: average GDP per capita growth, 2000-2015.

	(1) Full sample	(2) OECD	(3) Non-OECD	(4) High-income[a]	(5) Low-income[a]	(6) excluding high performing[b]
ln s^k	.013	.014	.022	- .014	.030**	.013
	(1.00)	(0.95)	(1.43)	(- 0.83)	(2.47)	(1.04)
ln x	- .015***	- .018***	- .012***	- .019***	- .011*	- .015***
	(- 5.70)	(- 5.57)	(- 3.04)	(- 5.24)	(- 2.00)	(- 4.92)
Test score	.0002***	.0001	.0002***	.0003***	.0002***	.0002***
	(3.77)	(1.64)	(3.52)	(4.91)	(3.54)	(2.55)
R^2 (adj.)	0.58	0.59	0.48	0.59	0.44	0.52
Countries	76	36	40	38	38	70

Notes: Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Regressions include regional dummies, an additional control for population growth, and a constant. $x =$ initial GDP per capita, s^k = ratio of investment to GDP, Test score = average value of all standardized mathematics and science PISA scores. Each variable refers to the average value for the period 2000-2015, except for initial GDP per capita which is measured in 2000. Countries are listed in the appendix.
[a]Defined by the countries that are above and below the median level ($9,943.85 in constant 2010 US$) of per capita GDP in 2000.
[b]Excluded: China, Finland, Hong Kong, Japan, Singapore, and South Korea.

Columns 2 and 3 split the sample into the 36 OECD and 40 non-OECD countries, respectively. Not surprisingly, the average PISA scores are insignificant in the OECD sample, but are highly significant in the non-OECD sample. This finding stresses the special importance of human capital quality in developing countries and is in line with Hanushek and Woessmann (2008, 2012), who observed that developing countries are somewhat more affected by cognitive skills than developed countries. Columns 4 and 5 divide the sample into the 38 countries that are above and below the median of GDP per capita in 2000. In both samples the estimates of the average score are positive and highly significant. However, education quality appears to be more important in the high-income sample. This is probably due to the presence of high performing economies, such as Macao and Singapore. In column 6 we exclude the top performing economies in our sample, that is those that achieve scores above 530 and are located on the far-right side of Figure 3, in order to examine whether the positive effect of cognitive skills is driven by these economies, which typically experience high growth rates as well. The estimate of cognitive skills remains positive and highly significant, implying that math and science scores do not simply reflect the high growth-high student performance relationship of overperforming countries. Finally, although the coefficient of initial GDP per capita is negative and significant across all samples, there is stronger evidence on conditional convergence for the OECD/high-income subgroups.

The growth impact of both quantitative and qualitative measures of human capital can be seen in Table 8. The table presents estimates for the 66 countries with required data on educational attainment and assessment scores over the decade 2000-2010. The first three columns include human capital as measured by mean years of schooling for the entire, male, and female population. These basic models show a significant association between school attainment and growth. Columns 4-6 substitute years of schooling for scores derived from international math and science assessments. Once again, there is a strong positive relationship with growth. Finally, columns 7-9 include both measures of human capital. We find that once assessment scores are included in

Table 8. Cross-country growth regressions: Years of schooling versus PISA test scores. Dependent variable: average GDP per capita growth, 2000-2010.

	Schooling only			Test scores only			Schooling and Test scores		
	(1) Total	(2) Males	(3) Females	(4) Total	(5) Males	(6) Females	(7) Total	(8) Males	(9) Females
cons	.112***	.106***	.124***	.127***	.133***	.122***	.112***	.116***	.111***
	(3.97)	(3.40)	(4.73)	(4.55)	(4.92)	(4.26)	(4.02)	(3.67)	(4.45)
D_{Asia}	.018*	.017*	.017*	.007	.007	.007	.009	.009	.008
	(1.90)	(1.84)	(1.92)	(0.85)	(0.87)	(0.85)	(1.20)	(1.23)	(1.12)
$D_{Lat.Am.}$	.006	.007	.005	.010*	.008	.011*	.010*	.009	.011*
	(1.04)	(1.11)	(0.85)	(1.67)	(1.45)	(1.88)	(1.75)	(1.50)	(1.92)
ln s^k	.023	.023	.023	.018	.019	.016	.018	.019	.016
	(1.66)	(1.66)	(1.64)	(1.23)	(1.34)	(1.13)	(1.19)	(1.28)	(1.11)
ln x	- .012***	- .012***	- .012***	- .016***	- .016***	- .016***	- .016***	- .016***	- .016***
	(- 4.88)	(- 4.92)	(- 4.80)	(- 5.24)	(- 5.16)	(- 5.36)	(- 5.09)	(- 5.06)	(- 5.22)
ln (T)	.028*						.010		
	(1.91)						(0.64)		
ln (M)		.030*						.010	
		(1.73)						(0.54)	
ln (F)			.023*						.007
			(1.87)						(0.60)
Test score total				.0002***			.0002**		
				(2.83)			(2.40)		
Test score males					.0002***			.0001**	
					(2.71)			(2.29)	
Test score females						.0002***			.0002**
						(2.98)			(2.59)
R^2 (adj.)	0.50	0.50	0.49	0.57	0.56	0.57	0.56	0.56	0.56
Countries					66				

Notes: Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. $x =$ initial GDP per capita, s^k = ratio of investment to GDP, T = total mean years of schooling, M & F = male & female mean years of schooling, Test score = average value of all standardized math and science PISA scores. Each variable refers to the average value for the decade 2000-2010, except for initial GDP per capita which is measured in 2000.

the regression, years of schooling are not significantly related to growth. On the other hand, cognitive skills remain positive and significant. This finding cannot and should not be interpreted as if schooling is insignificant for economic growth. It just emphasizes the fact that schooling leads to growth only when it actively increases cognitive skills (Hanushek and Kimko, 2000; Hanushek and Woessmann, 2008, 2012). The poor quality of schooling, which might not lead to the development of skills, has also been suggested by Pritchett (2001) as one of the possible reasons responsible for the failure of empirical analyses in establishing a robust positive link between human capital and growth. The results are similar when we disaggregate both human capital measures by gender, as male and female years of schooling become insignificant once we account for human capital quality. Considering the relatively small sample, and perhaps even more importantly, the short time period under study, the results reported in this section should not be interpreted as definite; it is better if they are viewed simply as indicative of the existing pattern. As more countries participate in international assessments, and do so for longer, the accuracy and robustness of the results will hopefully improve.

5.2. Endogeneity issues

A well-founded concern when estimating a growth regression similar to the one described in eq. (6), is that the growth relationships observed do not actually measure causal influences, but instead reflect reverse causality, omitted variables, measurement error, or even cultural differences. Specifically, endogeneity issues may arise as growth could possibly trigger investments in the educational system or increase family resources, which in turn lead to higher levels of educational achievement and improve cognitive skills. Following the analyses of Hanushek and Kimko (2000) and Hanushek and Woessmann (2008, 2012), we restrict the sample to countries that participated in the 2000 PISA survey, in order to rule out the possibility of simple reverse causality. This procedure reduces our sample to only 41 countries. The results are encouraging, as the estimates of the average test scores are still positive, albeit insignificant (see appendix Table A2). This provides some evidence against the hypothesis that the positive effect of cognitive skills on growth is simply the result of reverse causality.

Further evidence against this hypothesis comes from Hanushek and Kimko (2000) and Hanushek and Woessmann (2012), who fail to establish a robust connection across countries between resources devoted to education and the observed assessment scores.[21] In light of their finding, we make some comparisons across countries between government expenditure per lower secondary student and the average PISA score. The results are quite revealing (see Table 9). Estonia spent less than half and nearly a fifth of the amount that Cyprus and Luxembourg spent per lower secondary student in 2000, but it outscored both by 80 and 42 points respectively. Most strikingly, Slovakia spent 8.3 times less per lower secondary student compared to Luxembourg, yet both countries

[21] The authors report that inputs such as class size and expenditure per pupil have little to no effect in determining student achievement. The coefficient estimates for these variables are mostly insignificant, and in some cases, of the incorrect sign.

reached the same level of achievement. Therefore, educational expenditures are not systematically related to higher cognitive skills.

Table 9. Government spending versus PISA achievement.

	Government expenditure per lower secondary student (constant PPP$)		Average PISA score during 2000-2015
	In 2000	Average value during 2000-2012	
Cyprus	5,216.46	9,154.15	439.82
Estonia	2,643.56[a]	4,704.28	519.89
Japan	5,436.28	7,264.24	531.01
Luxembourg	13,682.53[b]	15,792.51	478.07
Slovakia	1,408.63	2,711.52	478.51
United States	7,536.08	9,731.24	492.04

Notes: The average PISA score refers to the simple average of all standardized math, science, and reading scores. Data on government expenditure per student are from the *World Bank EdStats*.
[a] Refers to the 2001 value.
[b] Refers to the 2003 value.

Another critical factor that cannot be measured, but may actually influence the estimates of the growth effect of human capital quality is cultural differences across countries.[22] In an attempt to explain the outstanding PISA performance of East Asian students, Jerrim (2015) studied the achievement of West-born children with East Asian descent. The author concluded that the substantial difference in performance between East Asian children and their Western counterparts cannot be attributed to variations in the educational systems alone. Thus, it is likely that cultural differences play a very important role in determining their high levels of achievement.[23] Finally, a few studies have tried to address the omitted variable bias by allowing policy (e.g. inflation rate, ratio of government consumption to GDP, ratio of public debt to GDP, terms of trade) and institutional variables (e.g. rule of law, democracy) to enter the growth regression (see, for example, Barro, 1998; Barro and Sala-i-Martin, 2004; Sala-i-Martin *et al.*, 2004). However, an in-depth investigation of the growth impact of the aforementioned policy and institutional features goes beyond the scope of this dissertation, since we are only interested in growth accounting within a specific growth model that takes a production function approach.[24] Besides, it is not clear how omission of these variables might influence the estimates of cognitive skills.

[22] In addition, a country's mean score may be influenced by the performance of immigrant students. On average across OECD countries, 12.5% of 15-year-old students in 2015 had an immigrant background compared to 9.4% in 2006 (OECD, 2016). In fact, the PISA 2009 results reported that the fraction of students with immigrant background was almost 15% in Singapore and more than 40% in Qatar (Altinok *et al*., 2018).
[23] A high value is placed on educational achievement across East Asia and there exists a belief that effort rather than innate ability is the key to success.
[24] Nevertheless, it is noteworthy to mention that after an extensive robustness analysis of 67 explanatory variables in growth regressions in a sample of 88 countries, Sala-i-Martin *et al*. (2004) report that the primary enrollment rate turns out to be the most influential factor (after an East Asian dummy) on per capita GDP growth.

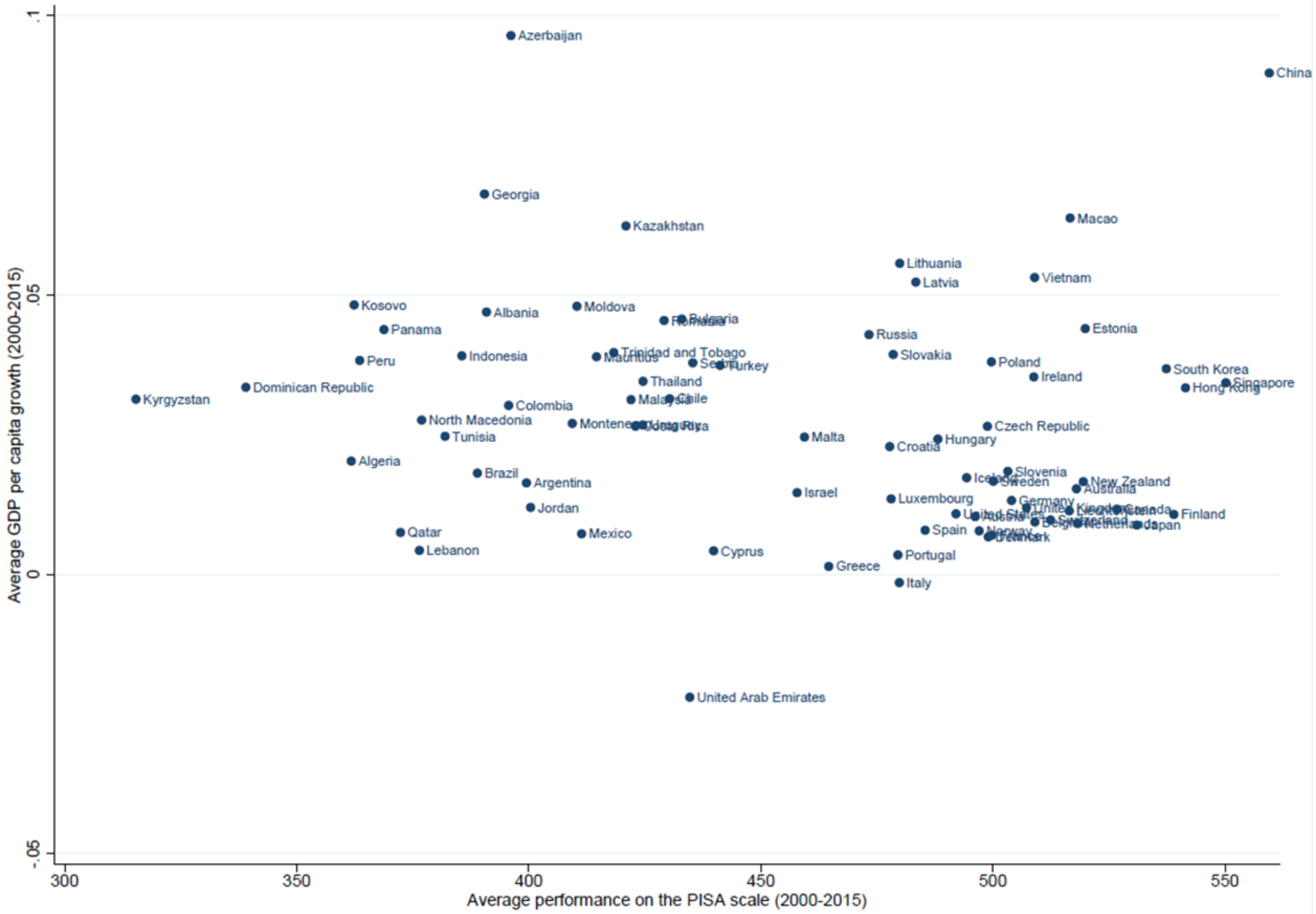

Figure 3. Average GDP per capita growth against average PISA performance in mathematics, science, and reading (2000-2015).

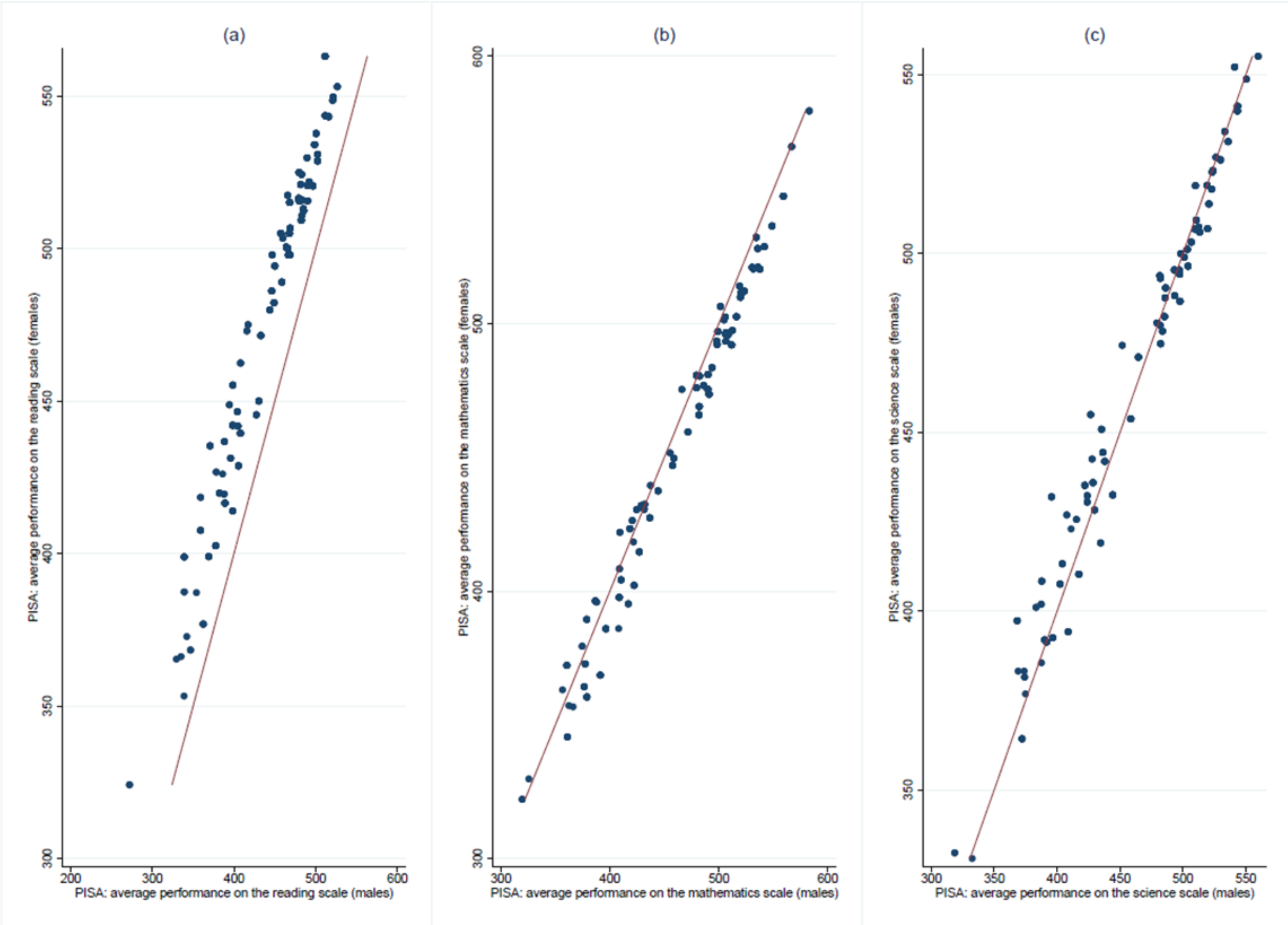

Figure 4. Average performance of females versus males in reading (a), mathematics (b), and science (c).

6. Generalized Additive Models (GAMs)

The bulk of cross-country growth studies are based on the assumption that all countries obey a common linear specification. However, Azariadis and Drazen (1990), Durlauf and Johnson (1995), and Kalaitzidakis *et al*. (2001) reject the cross-country linear model specification which underlies most of the empirical work on growth, pointing to the existence of threshold effects in the cross-country growth process. Obviously, one could easily estimate a linear model including polynomial terms, or other parametric transformations in the set of predictors to account for possible nonlinear and multi-modal responses. However, identification of the appropriate polynomial adjustments is often tedious and can lead to a highly correlated set of predictors, which depending on the situation, could create issues (e.g. one may be interested in evaluating the effect of changing variable z without changing z^2, z^3, etc.). Also, polynomial regression has a tendency to overfit, even on one dimensional data sets. The introduction of models that automatically identify appropriate transformations was an important step forward in regression analysis. This led to a wider generalization of linear models, known as Generalized Additive Models (henceforth GAMs; Hastie and Tibshirani, 1986, 1990).

GAMs extend the traditional Generalized Linear Models (GLMs), by allowing the determination of possible nonlinear effects of covariates on a response variable of interest. Therefore, the assumption of linearity between the response variable and the explanatory variables is relaxed. This flexibility, however, does not come without cost as there is arguably some loss in interpretability. The probability distribution of the response variable must still be specified, and in this respect, a GAM is parametric. In this sense they are more aptly named semiparametric models. In order to facilitate possible nonlinear relationships, smooth functions of predictors can be used instead of linear functions. In fact, the use of smooth terms is crucial since the functional shape of any relationship is rarely known *a priori* and the response variable may depend on the predictors in a complicated manner. It should be noted that smooth functions cannot be applied to non-continuous variables, and hence the linear predictor of a GAM may also include parametric terms, such as dummy and categorical variables. Consequently, some predictors can be modeled nonlinearly in addition to linear terms for other predictors. A GAM can be written as:

$$g\{E(Y)\} = \alpha + f_1(x_1) + f_2(x_2) + \cdots + f_p(x_p) + \varepsilon$$

where $g(\bullet)$ is a monotonic link function, α is the intercept and $f(\bullet)$ are functions which can be specified parametrically, nonparametrically, or even semi-parametrically, as smooth functions. As smooths different types of functions can be used (e.g. local linear regression, splines). Generally, splines have better mathematical properties and are most often used in GAM fitting. When applying GAMs, a crucial step is to select the appropriate level of smoothness for a predictor. This is best achieved through the concept of effective degrees of freedom (edf). If the degree of smoothness is too high then the data will be over-smoothed, whereas if it is too low the data will be under-smoothed. An advantage of using Wood's (2017) penalized likelihood approach over the back-fitting framework proposed by Hastie and Tibshirani (1990), is that the degree of smoothness can be automatically determined from the data as part of the model fitting process by generalized cross-validation (GCV), maximum likelihood methods, or another smoothness selection criterion (e.g. AIC). Nevertheless, there may also be situations where the degree of smoothness needs to be specified in advance. Another choice, albeit of secondary importance, is the basis dimension (k) used to represent smooth terms. This choice corresponds to setting an upper limit on the degrees of freedom allowed for each model term.[25] GAMs are fitted by penalized likelihood maximization and in practice this is achieved by penalized iteratively reweighted least squares (PIRLS).

6.1. Years of schooling

As in Kalaitzidakis *et al*. (2001) we allow the starting level of GDP per capita and the schooling variables to comprise the nonlinear components of the model, but we also emphasize the role of the investment rate as a variable with a potential to affect growth nonlinearly through possible thresholds. Essentially, we estimate a regression similar to the one described in eq. (6) with the principal difference being that initial income, investment-to-GDP, and educational attainment are modeled as smooth functions instead of linear functions. All variables mentioned above are expressed in natural logarithmic form. We model these data with the following GAM:

$$g\{E(y_{it})\} = \beta_0 + \beta_1 D_t + \beta_2 D_j + \beta_3 \ln(n_{it} + g + \delta_{it}) + s_1(\ln x_{it}) + s_2\left(\ln s_{it}^k\right) + s_3(\ln h_{it}) + \varepsilon_{it} \tag{8}$$

with smooth terms for initial GDP per capita, investment, and human capital (denoted by s_1, s_2 and s_3 respectively), and a linear term for the working age population growth.[26] Thin plate regression splines were used for the s functions.[27] Model (8) can flexibly determine the functional shape of the relationship between the response and the explanatory variables, avoiding the drawbacks of parametric modelling. In addition, we test a linear model (null hypothesis, eq. (6)) against the GAM alternative via an ANOVA test for goodness of fit.[28] The linear model is rejected against the GAM alternative in every case (see Table 10). This result is in accordance with previous empirical contributions that highlight the existence of nonlinearities in economic growth (Azariadis and Drazen, 1990; Durlauf and Johnson, 1995; Kalaitzidakis *et al*., 2001). Having established that the GAM specification is more appropriate, we proceed by estimating the model as given in eq. (8).

The estimates of the nonlinear components for the logarithms of initial income, investment rate, and years of schooling are presented graphically in Figures 5-8 alongside 95% pointwise confidence intervals. Notice that out of all human capital variables only female years of schooling, male post primary mean years of schooling, and female post primary mean years of schooling have a nonlinear connection to

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[25] Unless otherwise noted, the default k = 10 is used in model fitting.

[26] The model was fitted using the `gam()` function in R package `mgcv`, with integrated variable selection. A type of penalty-based model selection described in Marra and Wood (2011) is used.

[27] For a detailed discussion of the properties of thin plate regression splines, see Wood (2003, 2017).

[28] Comparisons between models were made on the basis of approximate F-tests (Hastie and Tibshirani, 1990).

growth. Given that the remaining measures of human capital are estimated to affect growth in a linear way (since they are modeled with less than two effective degrees of freedom), they are included in the linear part of the model. Figures 5a and 5b show a representative fit for initial GDP per capita and the ratio of investment to GDP, respectively. Both graphs are based on mean years of schooling for the whole population as the measure of human capital. It should be emphasized, however, that the shape of these graphs is remarkably robust to the alternative measures of human capital. Thus, for reasons of brevity, they are not presented. Figure 5a illustrates that the relationship between growth and initial GDP per capita is nonlinear. This is consistent with previous evidence on the existence of nonlinearities in the convergence process (Durlauf and Johnson, 1995; Quah, 1996; Liu and Stengos, 1999; Kalaitzidakis *et al.* 2001). The graph implies that with respect to the starting level of per capita GDP, the convergence hypothesis is only true for economies in the lower and the middle to upper income range, that is, for incomes below \$1000 and above \$8000. For countries in the lower to middle income range there is no evidence of convergence and in fact the relationship between growth and initial income is positive. Figure 5b shows the relationship between the investment-to-GDP ratio and per capita growth. Ignoring a small number of observations with low values, there is an evident positive relationship once the ratio of investment to GDP reaches 8%.

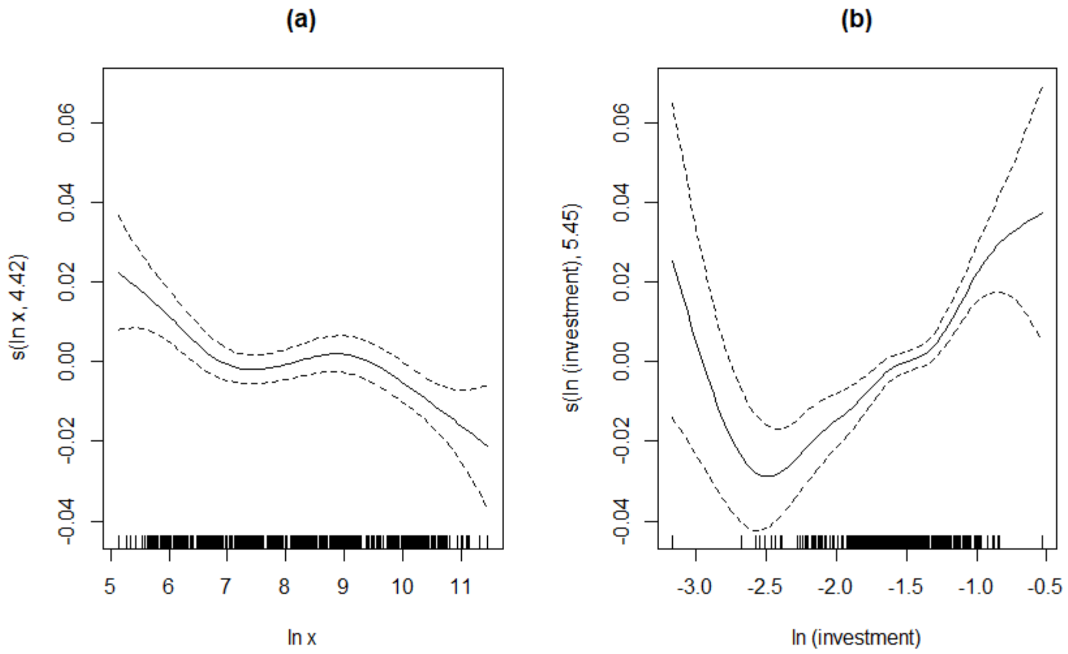

Figure 5. Fitted functions for initial GDP per capita (a) and the ratio of investment to GDP (b) for GDP per capita growth data. The dotted lines represent 95% pointwise confidence intervals. Each component function is vertically centered around zero. The number in brackets in each y-axis caption is the effective degrees of freedom of the term being plotted. The tick marks at the base of each panel indicate the predictor data.

With regard to the stock of human capital, we find that for female years of schooling there is a positive relationship throughout (Fig. 6). Figures 7 and 8 present estimates for male and female mean years of schooling at the post primary level, respectively. Surprisingly, there seems to be a positive relationship between 1 and 2.7 years of male post primary education, with the effect being negative for lower and higher values (Fig. 7). Increases in schooling have a positive effect on growth for economies with up to 2.2 years of female post primary education. However, there does not seem to be any relationship beyond this level (Fig. 8). Interestingly, even though the smooth functions for the schooling variables are significantly nonlinear (as evidenced by their approximate *p*-values[29]), a straight line falls within the confidence intervals in every case. This raises the question of whether the smooth terms should be included in the model at all. Consequently, the relationship between human capital and growth can be considered to be linear.

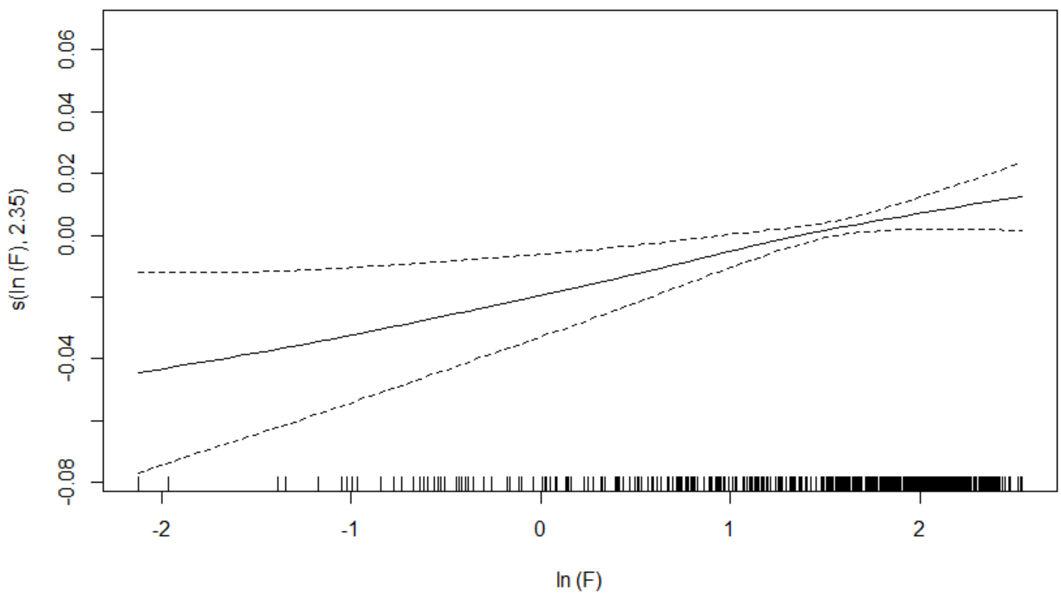

Figure 6. Fitted function for female mean years of schooling (F) for GDP per capita growth data. The dotted lines represent 95% pointwise confidence intervals. The function is vertically centered around zero. The number in brackets in the y-axis caption is the effective degrees of freedom of the term being plotted. The tick marks at the base of the panel indicate the predictor data.

[29] *P*-value computation for the individual smooth terms is not straightforward, due to the effects of penalization, but approximations are available.

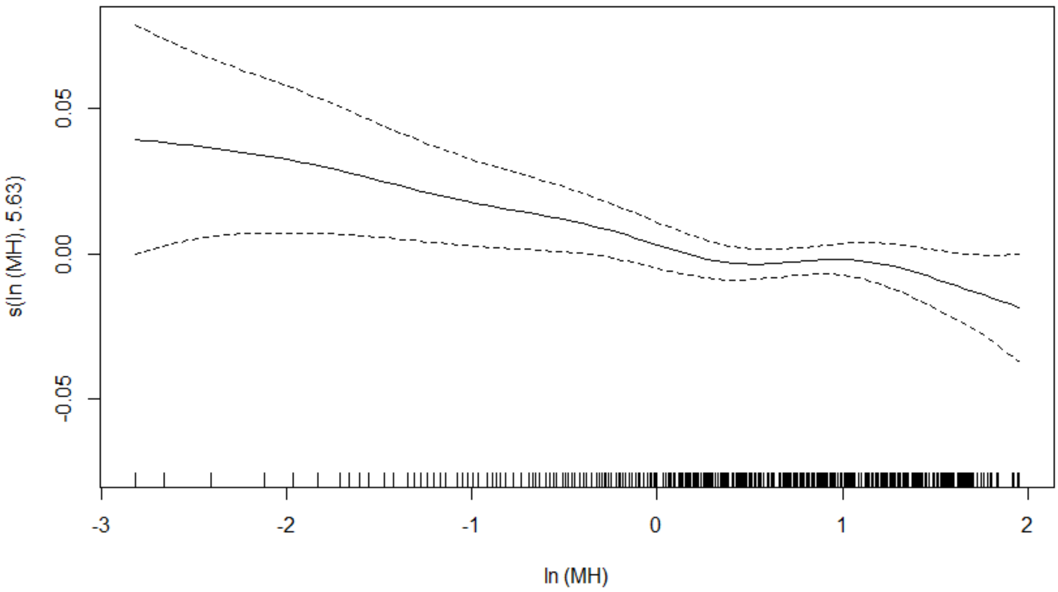

Figure 7. Fitted function for male mean years of schooling at the post primary level (MH) for GDP per capita growth data. The dotted lines represent 95% pointwise confidence intervals. The function is vertically centered around zero. The number in brackets in the y-axis caption is the effective degrees of freedom of the term being plotted. The tick marks at the base of the panel indicate the predictor data.

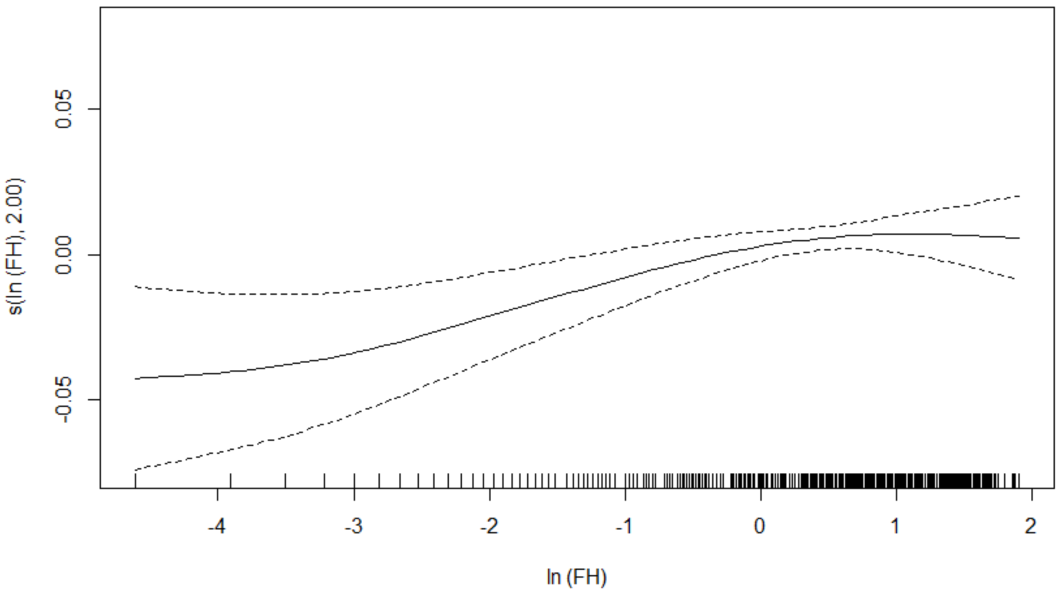

Figure 8. Fitted function for female mean years of schooling at the post primary level (FH) for GDP per capita growth data. The dotted lines represent 95% pointwise confidence intervals. The function is vertically centered around zero. The number in brackets in the y-axis caption is the effective degrees of freedom of the term being plotted. The tick marks at the base of the panel indicate the predictor data.

Table 10. Generalized Additive Models: Barro & Lee human capital. Dependent variable: GDP per capita growth, 1970-2010.

	(1) T	(2) M & F	(3) TPR & TH	(4) MPR & FPR	(5) MH & FH
cons	.047***	.077***	.039***	.053***	.045***
	(3.27)	(4.19)	(2.72)	(3.56)	(3.11)
D_{1970}	.005	.004	.003	.005	.002
	(1.38)	(1.03)	(0.69)	(1.64)	(0.54)
D_{1980}	- .014***	- .015***	- .015***	- .014***	- .016***
	(- 4.67)	(- 4.83)	(- 4.99)	(- 4.70)	(- 5.12)
D_{1990}	- .012***	- .013***	- .013***	- .012***	- .014***
	(- 4.44)	(- 4.59)	(- 4.75)	(- 4.53)	(- 4.88)
D_{Africa}	- .012***	- .014***	- .015***	- .013***	- .014***
	(- 3.62)	(- 4.13)	(- 4.32)	(- 4.04)	(- 4.06)
$D_{Lat.Am.}$	- .010***	- .013***	- .012***	- .012***	- .013***
	(- 3.14)	(- 3.87)	(- 3.88)	(- 3.77)	(- 3.75)
ln $(n+g+\delta)$	.010*	.008	.007	.010*	.005
	(1.81)	(1.40)	(1.37)	(1.78)	(0.82)
ln (T)	.005*				
	(1.95)				
ln (M)		- .014**			
		(- 2.02)			
ln (TPR)			.012***		
			(3.84)		
ln (TH)			- .005**		
			(- 2.05)		
ln (MPR)				- .008	
				(- 1.00)	
ln (FPR)				.012**	
				(2.37)	

Approximate significance of smooth terms

	edf	*p*-value	edf	*p*-value	edf	*p*-value	edf	*p*-value	edf	*p*-value
ln x	4.42	3.51e-06	4.40	9.79e-06	4.71	8.73e-05	4.57	1.12e-07	4.46	0.0004
ln s^k	5.45	5.43e-14	5.42	9.71e-13	6.62	8.51e-14	5.67	1.02e-12	5.95	5.85e-14
ln (F)			2.35	0.0044						
ln (MH)									5.63	0.0023
ln (FH)									2.00	0.0004

	(1)	(2)	(3)	(4)	(5)
R^2 (adj.)	0.32	0.33	0.34	0.335	0.344
Deviance explained	34.7%	35.9%	36.8%	36.1%	37.7%
GCV	.0005	.0005	.0005	.0005	.0005
ANOVA-test	5.61	4.69	4.89	5.49	4.07
Approx. p-value	1.017e-06	4.867e-06	2.069e-06	9.191e-07	1.091e-06
Observations			467		
Countries			134		

Notes: t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. x = initial GDP per capita, s^k = ratio of investment to GDP, T = total mean years of schooling, TPR & TH = total mean years of schooling at the primary & at the post primary level, M & F = male & female mean years of schooling, MPR & FPR = male & female mean years of schooling at the primary level, MH & FH = male & female mean years of schooling at the post primary level. Countries are listed in the appendix.

6.2. Cognitive skills

Similar to the previous section, we allow the initial level of GDP per capita, the investment-to-GDP ratio, and the human capital quality variables to make up the nonlinear components of the model, whereas population growth is taken to be linear. Again, we should note that Figures 9a and 9b are based on the performance in mathematics as the measure of human capital quality. The shape of these graphs is, however, robust to the alternative measures of cognitive skills (not shown). As it is clear from Figure 9a, the relationship between per capita growth and initial income is nonlinear. The plot suggests that the convergence hypothesis holds for countries with initial per capita income above $1800. For countries with per capita income lower than $1800 there is no evidence of convergence. With regard to investment it turns out that only after the ratio reaches approximately 22% there is a positive contribution to economic growth. For countries with investment rates lower than 22% the effect is negative (Fig. 9b). Figure 10 presents the fit for the average mathematics test score. For low values, performance in mathematics seems to have a negative impact on growth. Once it surpasses the 350-point level, however, the relationship turns positive and continues to be positive to the highest levels of achievement. The same pattern holds for female performance in mathematics (Fig. 11), but the nonlinear component is in this case insignificant. Performance in science and reading both as a whole and subdivided by gender are estimated to affect growth linearly. Finally, the ANOVA goodness of fit test suggests that a GAM with nonlinear effects for the starting level of per capita GDP and the share of output allocated to investment is favored over the linear model alternative across all specifications.

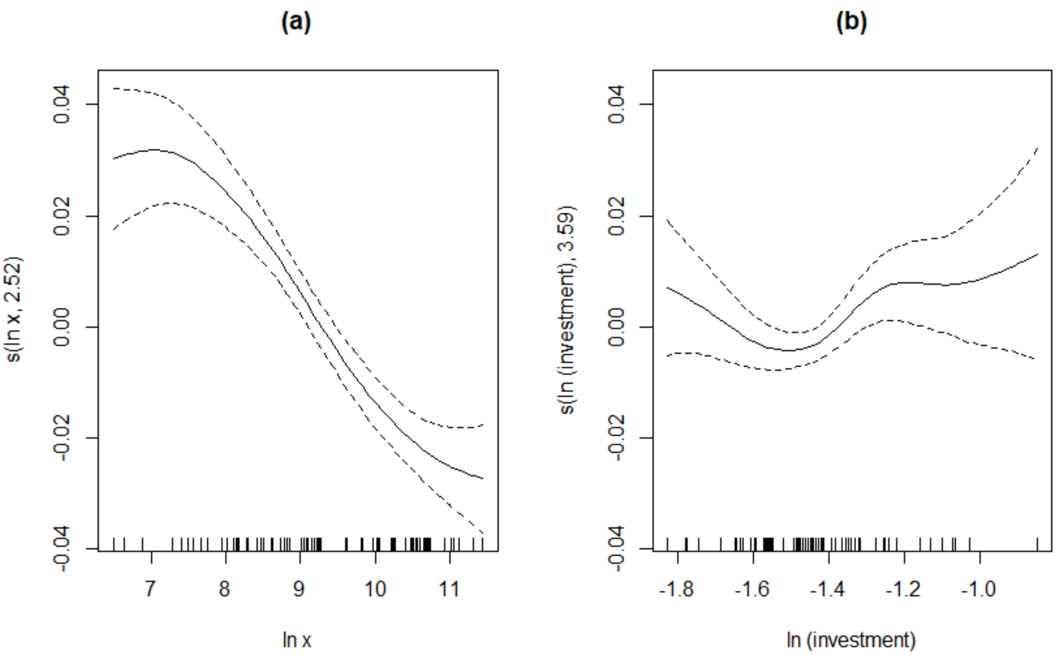

Figure 9. Fitted functions for initial GDP per capita (a) and the ratio of investment to GDP (b) for GDP per capita growth data. The dotted lines represent 95% pointwise confidence intervals. Each component function is vertically centered around zero. The number in brackets in each y-axis caption is the effective degrees of freedom of the term being plotted. The tick marks at the base of each panel indicate the predictor data.

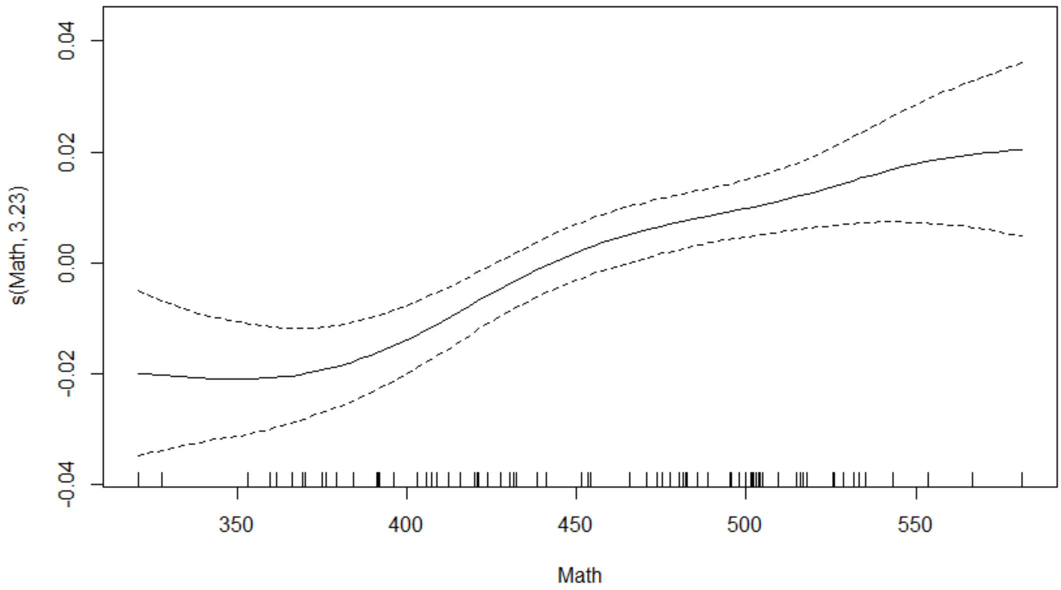

Figure 10. Fitted function for PISA performance on the mathematics scale for GDP per capita growth data. The dotted lines represent 95% pointwise confidence intervals. The function is vertically centered around zero. The number in brackets in the y-axis caption is the effective degrees of freedom of the term being plotted. The tick marks at the base of the panel indicate the predictor data.

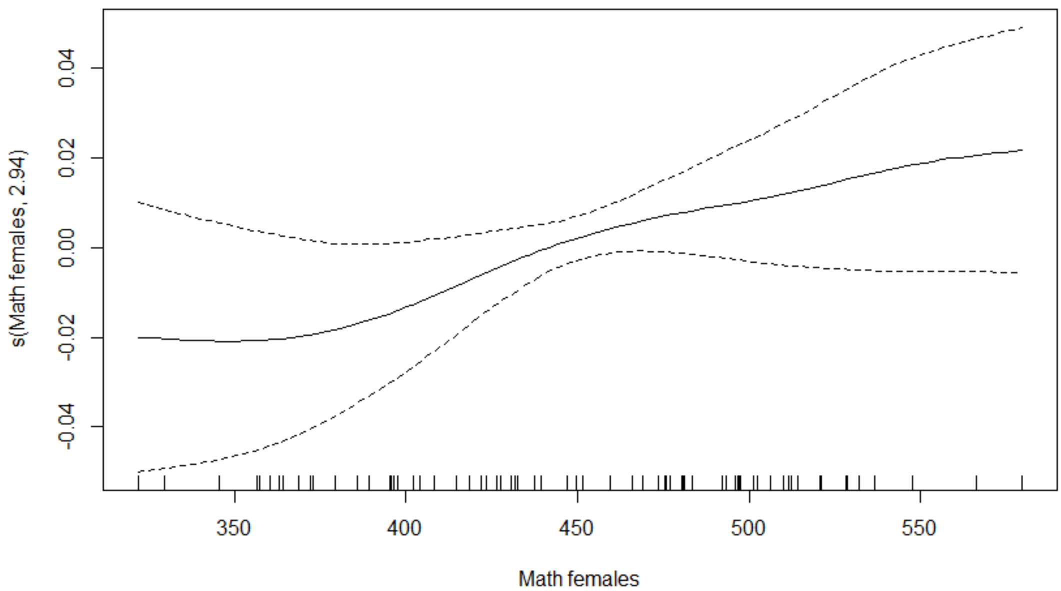

Figure 11. Fitted function for PISA performance on the mathematics scale (females) for GDP per capita growth data. The dotted lines represent 95% pointwise confidence intervals. The function is vertically centered around zero. The number in brackets in the y-axis caption is the effective degrees of freedom of the term being plotted. The tick marks at the base of the panel indicate the predictor data.

Table 11. Generalized Additive Models: PISA test scores. Dependent variable: average GDP per capita growth, 2000-2015.

	(1) Math	(2) Math males & females	(3) Science	(4) Science males & females	(5) Reading	(6) Reading males & females
cons	.035**	3.337e-02	- 3.432e-02	- 2.747e-02	- 3.313e-02	- 2.755e-02
	(2.17)	(0.59)	(- 1.62)	(- 1.15)	(- 1.61)	(- 1.27)
D_{Asia}	- .001	- 1.360e-03	4.621e-03	4.153e-03	4.571e-03	3.171e-03
	(- 0.18)	(- 0.24)	(0.80)	(0.71)	(0.79)	(0.53)
$D_{Lat.Am.}$	.007	8.005e-03	2.462e-04	- 1.913e-03	- 1.663e-03	- 3.518e-03
	(1.30)	(1.46)	(0.05)	(- 0.30)	(- 0.32)	(- 0.62)
$\ln(n+g+\delta)$	.003	3.593e-03	- 5.601e-03	- 5.216e-03	- 4.978e-03	- 5.337e-03
	(0.54)	(0.59)	(- 0.83)	(- 0.77)	(- 0.72)	(- 0.77)
Math males		5.806e-06				
		(0.05)				
Science			1.017e-04**			
			(2.07)			
Science males				1.765e-04		
				(0.95)		
Science females				- 8.579e-05		
				(- 0.42)		
Reading					1.051e-04**	
					(2.13)	
Reading males						1.823e-04
						(1.24)
Reading females						- 7.996e-05
						(- 0.52)

Approximate significance of smooth terms

	edf	p-value	edf	p-value	edf	p-value	edf	p-value	edf	p-value	edf	p-value
$\ln x$	2.52	4.11e-14	2.48	1.53e-14	2.00	2.24e-08	2.00	1.95e-08	2.06	3.79e-08	2.07	3.21e-08
$\ln s^k$	3.59	0.015	3.49	0.023	4.16	0.018	3.93	0.016	3.89	0.014	3.67	0.012
Math	3.23	6.43e-06										
Math females			2.94	0.101								
R^2 (adj.)	0.70		0.70		0.61		0.61		0.61		0.61	
Deviance explained	75%		75.4%		66.2%		66.3%		66%		66.3%	
GCV	.0002		.0002		.0002		.0002		.0002		.0002	
ANOVA-test	3.66		3.41		3.78		3.97		3.94		4.17	
Approx. p-value	0.003		0.006		0.007		0.006		0.006		0.005	
Countries							76					

Notes: t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. x = initial GDP per capita, s^k = ratio of investment to GDP. Math, Science, and Reading = PISA performance on the mathematics, science, and reading scale, respectively. Countries are listed in the appendix.

One additional point is worth discussing. In the results reported earlier the basis dimension for each smooth term was set by default to 10 (implying a maximum of 9 degrees of freedom; the basis dimension minus one degree of freedom due to the identifiability constraint[30] on each smooth term). However, a space of functions of dimension 20 will contain a larger subspace of functions with, say, 5 effective degrees of freedom than will a function space of dimension 10. Hence, it is often the case that increasing k will change the effective degrees of freedom estimated for a term, even though both old and new estimated degrees of freedom are lower than the original $k - 1$. In light of this, we set $k = 20$ in order to examine whether the results are sensitive to the choice of basis dimension. As expected, when the stock of human capital is considered, there is little to no difference with respect to Table 10 (see appendix Table A3). The resulting plots are almost indistinguishable from those reported for the default k value, and thus are not presented. As far as human capital quality is concerned, there are some noticeable differences, since initial income is modeled with more edf and performance on the reading scale is specified as significantly nonlinear (see appendix Table A4). This does not come as a surprise, since increasing the number of basis dimension typically yields wigglier nonlinear estimates. The plots for the remaining variables (i.e. investment rate and performance in mathematics) are almost identical to those presented earlier in this section, and therefore not shown. This leads to the conclusion that the smooth estimates of cognitive skills are somewhat sensitive to the choice of basis dimension.

7. Conclusions

A vast literature in education economics reports positive estimates of educational attainment, whether proxied by literacy rates, school enrollment ratios, or mean years of schooling. The impact of education on economic growth, however, remains controversial. This is because coefficient estimates are sensitive to the type of data used, the time frame, the model specification, and the measurement of human capital. This dissertation analyzes the growth effects of education in a panel of 134 economies observed from 1970 to 2010. The first measure we employ is the one encountered most frequently in empirical growth studies, i.e. mean years of schooling. We find that mean years of schooling for the total population are positively and significantly related to growth. We also consider differences by education level and gender. The results indicate that most measures of male education are negative and significant, whereas female education has a significant positive effect on growth. Our work also provides evidence on the widely discussed topic of conditional convergence.

In addition to the quantitative measure of human capital, we also investigate the growth impact of a qualitative measure. Data on students' scores on the internationally comparable PISA survey were used to proxy the quality of human capital in 76 economies from 2000 to 2015. Even though scores in all academic subjects are positive and significant, performance in mathematics seems to be somewhat more important, at

[30] The identifiability constraint is that the sum of the values of each curve, at the observed covariate values, must be zero. For a straight line, this condition determines exactly where the line must pass through zero, so there can be no uncertainty about this point.

least quantitatively. Next, we focus on mathematics and science performance and examine whether the results are driven by specific subgroups of countries. We find a larger impact of cognitive skills in high-income countries. Moreover, when the qualitative dimension of human capital is considered in conjunction with the quantitative dimension, the effect of cognitive skills remains positive and significant, whereas years of schooling for the total, male and female population are rendered insignificant. This finding represents a growing consensus in the education literature that school attainment promotes growth only when it effectively increases cognitive skills.

Several researchers corroborate the presence of threshold effects in economic development, due to the attainment of critical mass in human capital and other state variables. Motivated by theories emphasizing threshold externalities, we estimate a Generalized Additive Model that allows for graphical representation of possible nonlinear effects on growth. Initial income, investment rate, and human capital (whether proxied by mean years of schooling or assessment scores) comprise the nonlinear components of the model. Out of all school attainment variables only female mean years of schooling both as a whole and at the post primary level and male mean years of schooling at the post primary level affect growth in a nonlinear way. In contrast, initial per capita income and investment rate have a robust nonlinear effect on economic growth across all specifications. Regarding the quality of human capital, only performance in mathematics seems to have a nonlinear impact on growth, while performance in science and reading can be considered to be linear. In sum, the analysis here provides little evidence for a nonlinear relationship between human capital and growth. We, therefore, conclude that the nonlinearities present in our sample arise mainly from two sources: the initial level of GDP per capita and the ratio of investment to GDP.

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Appendix

Table A1. OLS regressions (Full sample): Barro & Lee human capital. Dependent variable: average GDP per capita growth, 1970-2010.

	(1) T	(2) M & F	(3) TPR & TH	(4) MPR & FPR	(5) MH & FH
cons	.105***	.116***	.096***	.114***	.108***
	(6.20)	(6.55)	(5.67)	(6.30)	(6.26)
D_{1970}	.009**	.008**	.006	.010***	.006
	(2.49)	(2.29)	(1.55)	(2.91)	(1.59)
D_{1980}	- .014***	- .014***	- .016***	- .014***	- .015***
	(- 4.98)	(- 5.04)	(- 5.41)	(- 5.10)	(- 5.11)
D_{1990}	- .010***	- .010***	- .011***	- .010***	- .010***
	(- 3.18)	(- 3.27)	(- 3.44)	(- 3.33)	(- 3.30)
D_{Africa}	- .014***	- .016***	- .017***	- .015***	- .017***
	(- 3.89)	(- 4.52)	(- 4.77)	(- 4.16)	(- 4.83)
$D_{Lat.Am.}$	- .010***	- .013***	- .013***	- .013***	- .014***
	(- 3.46)	(- 4.03)	(- 4.42)	(- 4.03)	(- 4.15)
ln s^k	.024***	.023***	.024***	.022***	.024***
	(3.71)	(3.36)	(3.59)	(3.33)	(3.69)
ln $(n + g + \delta)$	.005	.003	.004	.005	.0004
	(0.63)	(0.37)	(0.49)	(0.62)	(0.05)
ln x	- .004***	- .005***	- .004***	- .005***	- .004***
	(- 3.27)	(- 3.50)	(- 2.94)	(- 4.12)	(- 2.63)
ln (T)	.006**				
	(1.97)				
ln (M)		- .015*			
		(- 1.84)			
ln (F)		.014**			
		(2.51)			
ln (TPR)			.013***		
			(4.26)		
ln (TH)			- .006**		
			(- 1.96)		
ln (MPR)				- .006	
				(- 0.69)	
ln (FPR)				.011*	
				(1.83)	
ln (MH)					- .015***
					(- 2.68)
ln (FH)					.011**
					(2.52)
R^2 (adj.)	0.24	0.25	0.26	0.25	0.25
Observations			490		
Countries			142		

Notes: Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. x = initial GDP per capita, s^k = ratio of investment to GDP, T = total mean years of schooling, TPR & TH = total mean years of schooling at the primary & at the post primary level, M & F = male & female mean years of schooling, MPR & FPR = male & female mean years of schooling at the primary level, MH & FH = male & female mean years of schooling at the post primary level. Countries are listed in the appendix.

Table A2. Cross-section regressions: PISA test scores. Dependent variable: average GDP per capita growth, 2000-2015.

	(1) Math	(2) Math males & females	(3) Science	(4) Science males & females	(5) Reading	(6) Reading males & females
ln x	- .014*** (- 5.30)	- .015*** (- 5.05)	- .013*** (- 5.48)	- .013*** (- 5.22)	- .013*** (- 4.64)	- .014*** (- 4.58)
Math	.0001* (1.75)					
Math males		.0002 (1.06)				
Math females		- .0001 (- 0.44)				
Science			.0001 (1.45)			
Science males				- .00004 (- 0.27)		
Science females				.0001 (0.78)		
Reading					.0001 (1.16)	
Reading males						.0001 (0.88)
Reading females						- .00004 (- 0.33)
R^2 (adj.)	0.63	0.62	0.62	0.61	0.61	0.60
Countries	41					

Notes: Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Regressions include regional dummies, additional controls for the ratio of investment to GDP and population growth, and a constant. $x =$ initial GDP per capita. Math, Science, and Reading = PISA performance on the mathematics, science, and reading scale, respectively. Each variable is measured in 2000.

Table A3. Generalized Additive Models ($k = 20$): Barro & Lee human capital. Dependent variable: GDP per capita growth, 1970-2010.

	(1) T	(2) M & F	(3) TPR & TH	(4) MPR & FPR	(5) MH & FH
cons	.045*** (3.16)	.081*** (4.28)	.038*** (2.67)	.051*** (3.43)	.044*** (3.00)
D_{1970}	.005 (1.43)	.004 (1.12)	.002 (0.68)	.006* (1.70)	.002 (0.57)
D_{1980}	- .014*** (- 4.60)	- .014*** (- 4.69)	- .015*** (- 4.99)	- .014*** (- 4.60)	- .016*** (- 5.05)
D_{1990}	- .012*** (- 4.41)	- .013*** (- 4.53)	- .013*** (- 4.75)	- .012*** (- 4.50)	- .013*** (- 4.87)
D_{Africa}	- .012*** (- 3.60)	- .014*** (- 4.18)	- .015*** (- 4.34)	- .013*** (- 4.04)	- .014*** (- 4.06)
$D_{Lat.Am.}$	- .010*** (- 3.17)	- .013*** (- 4.03)	- .012*** (- 3.88)	- .012*** (- 3.83)	- .013*** (- 3.82)
ln $(n + g + \delta)$	.009* (1.71)	.007 (1.28)	.007 (1.33)	.009 (1.63)	.004 (0.71)
ln (T)	.005* (1.96)				
ln (M)		- .018** (- 2.36)			
ln (TPR)			.012*** (3.88)		
ln (TH)			- .005** (- 2.08)		
ln (MPR)				- .008 (- 1.08)	
ln (FPR)				.012** (2.47)	

Approximate significance of smooth terms

	edf	*p*-value	edf	*p*-value	edf	*p*-value	edf	*p*-value	edf	*p*-value
ln x	4.80	3.36e-06	5.07	6.65e-06	4.47	5.86e-05	4.61	6.89e-08	4.23	0.0002
ln s^k	6.73	4.13e-14	7.07	8.93e-13	7.85	8.86e-14	7.60	7.09e-13	7.87	6.11e-14
ln (F)			2.54	0.0024						
ln (MH)									5.26	0.0013
ln (FH)									2.21	0.0004
R^2 (adj.)	0.33		0.34		0.34		0.34		0.35	
Deviance explained	35.3%		36.9%		37.1%		37%		38.5%	
GCV	.0005		.0005		.0005		.0005		.0005	
ANOVA-test	5.12		4.30		4.66		5.05		4.05	
Approx. p-value	7.024e-07		2.392e-06		1.847e-06		4.349e-07		4.124e-07	
Observations					467					
Countries					134					

Notes: t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. x = initial GDP per capita, s^k = ratio of investment to GDP, T = total mean years of schooling, TPR & TH = total mean years of schooling at the primary & at the post primary level, M & F = male & female mean years of schooling, MPR & FPR = male & female mean years of schooling at the primary level, MH & FH = male & female mean years of schooling at the post primary level. Countries are listed in the appendix.

Table A4. Generalized Additive Models ($k = 20$): PISA test scores. Dependent variable: average GDP per capita growth, 2000-2015.

	(1) Math	(2) Math males & females	(3) Science	(4) Science males & females	(5) Reading	(6) Reading males & females
Math males		- 7.453e-05 (- 0.65)				
Science			1.497e-04*** (3.08)			
Science males				9.746e-05 (0.56)		
Science females				4.991e-05 (0.26)		
Reading males						1.233e-04 (0.89)
Reading females						2.234e-05 (0.15)

Approximate significance of smooth terms

	(1) edf	(1) p-value	(2) edf	(2) p-value	(3) edf	(3) p-value	(4) edf	(4) p-value	(5) edf	(5) p-value	(6) edf	(6) p-value
ln x	10.2	9.05e-15	10.0	1.07e-15	10.9	4.1e-09	10.7	6.51e-09	9.93	2.8e-09	10.8	2.15e-08
ln s^k	3.86	0.035	3.67	0.083	2.92	0.155	2.88	0.169	3.75	0.071	3.00	0.099
Math	3.00	7.21e-07										
Math females			2.88	0.006								
Reading									6.71	0.009		

	(1)	(2)	(3)	(4)	(5)	(6)
R^2 (adj.)	0.76	0.77	0.69	0.68	0.71	0.68
Deviance explained	82.5%	83.1%	76%	76%	80%	76.1%
GCV	.0001	.0001	.0002	.0002	.0002	.0002
ANOVA-test	3.75	3.75	3.65	3.61	3.26	3.56
Approx. p-value	0.0002	0.0002	0.0005	0.0006	0.0005	0.0006
Countries	76					

Notes: t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Regressions include regional dummies, an additional control for population growth, and a constant. x = initial GDP per capita, s^k = ratio of investment to GDP. Math, Science, and Reading = PISA performance on the mathematics, science, and reading scale, respectively. Countries are listed in the appendix.

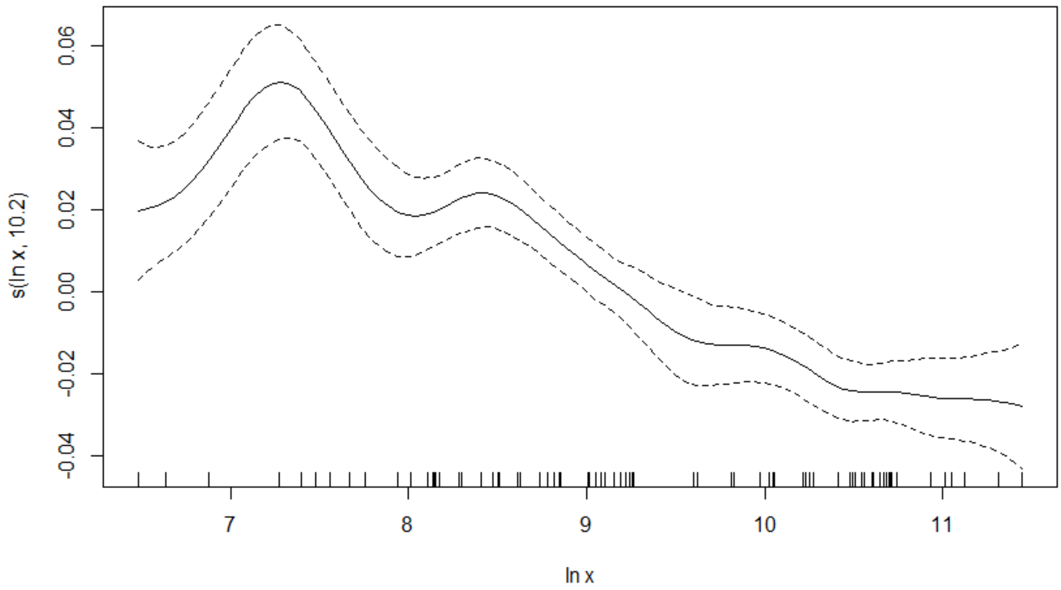

Figure 12. Fitted function for initial GDP per capita for GDP per capita growth data. The dotted lines represent 95% pointwise confidence intervals. The function is vertically centered around zero. The number in brackets in the y-axis caption is the effective degrees of freedom of the term being plotted. The tick marks at the base of the panel indicate the predictor data.

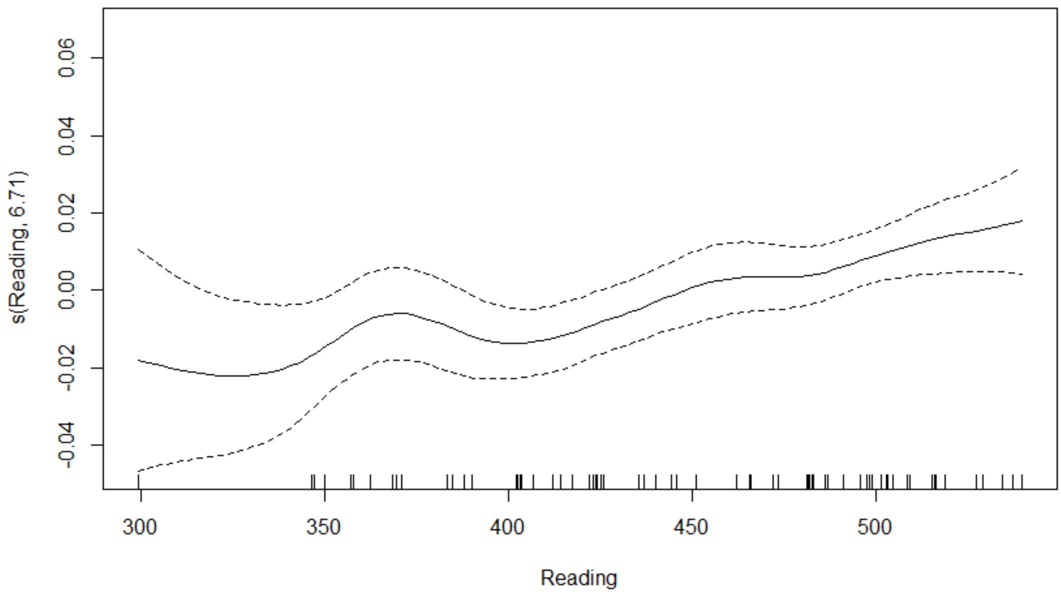

Figure 13. Fitted function for PISA performance on the reading scale for GDP per capita growth data. The dotted lines represent 95% pointwise confidence intervals. The function is vertically centered around zero. The number in brackets in the y-axis caption is the effective degrees of freedom of the term being plotted. The tick marks at the base of the panel indicate the predictor data.

Table A5. List of countries with available educational attainment and economic data.

1	Afghanistan	49	Guatemala	97	Pakistan
2	Albania	50	Guyana	98	Panama
3	Algeria	51	Haiti	99	Papua New Guinea
4	Argentina	52	Honduras	100	Paraguay
5	Armenia	53	Hong Kong SAR	101	Peru
6	Australia	54	Hungary	102	Philippines
7	Austria	55	Iceland	103	Poland
8	Bahrain	56	India	104	Portugal
9	Bangladesh	57	Indonesia	105	Qatar
10	Barbados	58	Iran	106	Republic of Korea
11	Belgium	59	Iraq	107	Romania
12	Belize	60	Ireland	108	Russian Federation
13	Benin	61	Israel	109	Rwanda
14	Bolivia	62	Italy	110	Saudi Arabia
15	Botswana	63	Jamaica	111	Senegal
16	Brazil	64	Japan	112	Serbia
17	Brunei Darussalam	65	Jordan	113	Sierra Leone
18	Bulgaria	66	Kazakhstan	114	Singapore
19	Burundi	67	Kenya	115	Slovakia
20	Cambodia	68	Kuwait	116	Slovenia
21	Cameroon	69	Kyrgyzstan	117	South Africa
22	Canada	70	Lao PDR	118	Spain
23	Central African Republic	71	Latvia	119	Sri Lanka
24	Chile	72	Lesotho	120	Sudan
25	China	73	Liberia	121	Swaziland
26	Colombia	74	Libya	122	Sweden
27	Congo Democratic Republic	75	Lithuania	123	Switzerland
28	Congo Republic	76	Luxembourg	124	Tajikistan
29	Costa Rica	77	Macao SAR	125	Tanzania
30	Cote d'Ivoire	78	Malawi	126	Thailand
31	Croatia	79	Malaysia	127	Togo
32	Cuba	80	Mali	128	Tonga
33	Cyprus	81	Malta	129	Trinidad and Tobago
34	Czech Republic	82	Mauritania	130	Tunisia
35	Denmark	83	Mauritius	131	Turkey
36	Dominican Republic	84	Mexico	132	Uganda
37	Ecuador	85	Moldova	133	Ukraine
38	Egypt	86	Mongolia	134	United Arab Emirates
39	El Salvador	87	Morocco	135	United Kingdom
40	Estonia	88	Mozambique	136	United States
41	Fiji	89	Myanmar	137	Uruguay
42	Finland	90	Namibia	138	Venezuela
43	France	91	Nepal	139	Vietnam
44	Gabon	92	Netherlands	140	Yemen
45	Gambia	93	New Zealand	141	Zambia
46	Germany	94	Nicaragua	142	Zimbabwe
47	Ghana	95	Niger		
48	Greece	96	Norway		

Table A5. continued.

Non-oil sample: As in full sample, except Bahrain, Gabon, Iran, Iraq, Kuwait, Libya, Saudi Arabia, and United Arab Emirates.

Notes: SAR = Special Administrative Region, PDR = People's Democratic Republic.

Table A6. List of countries with available cognitive skills and economic data.

1	Albania	27	Hungary	53	Norway
2	Algeria	28	Iceland	54	Panama
3	Argentina	29	Indonesia	55	Peru
4	Australia	30	Ireland	56	Poland
5	Austria	31	Israel	57	Portugal
6	Azerbaijan	32	Italy	58	Qatar
7	Belgium	33	Japan	59	Republic of Korea
8	Brazil	34	Jordan	60	Romania
9	Bulgaria	35	Kazakhstan	61	Russian Federation
10	Canada	36	Kosovo	62	Serbia
11	Chile	37	Kyrgyzstan	63	Singapore
12	China	38	Latvia	64	Slovakia
13	Colombia	39	Lebanon	65	Slovenia
14	Costa Rica	40	Liechtenstein	66	Spain
15	Croatia	41	Lithuania	67	Sweden
16	Cyprus	42	Luxembourg	68	Switzerland
17	Czech Republic	43	Macao SAR	69	Thailand
18	Denmark	44	North Macedonia	70	Trinidad and Tobago
19	Dominican Republic	45	Malaysia	71	Tunisia
20	Estonia	46	Malta	72	Turkey
21	Finland	47	Mauritius	73	United Arab Emirates
22	France	48	Mexico	74	United Kingdom
23	Georgia	49	Moldova	75	United States
24	Germany	50	Montenegro	76	Uruguay
25	Greece	51	Netherlands	77	Vietnam
26	Hong Kong SAR	52	New Zealand		

Notes: SAR = Special Administrative Region.

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