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Converging to Convergence: The Role of Human Capital

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Converging to Convergence: The Role of Human Capital*

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Abstract

This paper analyses $\sigma-$convergence and absolute $\beta-$convergence in human capital indicators in a sample of 140 countries from 1970 to 2020. The literature has found some evidence of absolute convergence in per capita income since 2000s. As convergence in human capital preceded convergence in per capita income, human capital may have played a role in this process. We find that the coefficient of $\beta-$convergence in per capita income, conditional on the initial level of human capital, is twice as high as the $\beta-$coefficient of unconditional convergence. The difference between both coefficients accounts for the role of human capital in explaining absolute convergence in per capita income in recent decades. When we control for institutions, the difference between absolute and conditional convergence is very low, suggesting that human capital has played a greater role in the speed of convergence. The results hold with alternative measures of human capital and development, and are robust to the inclusion of fixed effects and regional dummies to account for omitted variables.

Keywords: convergence, GDP per capita, human capital, years of schooling.

JEL Classification: O11, O15, O4, O47.

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1. Introduction

Whether poor countries converge to the income level of rich economies has captured the attention of researchers for many years. Evidence of absolute convergence, in the sense that poor countries unconditionally catch up the income levels of rich economies, has not been found in the literature for many decades (Baumol, 1986; De Long, 1988; Barro, 1991; Pritchett, 1997; Rodrick, 2013). However, new evidence shows signals of unconditional convergence from 2000 onward (Kremer et al., 2021; Patel et al., 2021). In this paper we focus on convergence in human capital, and whether it has played any role in the recent convergence of income per capita observed in the data. Our results show that this is the case. Human capital is not only an important determinant of growth rates but has also helped to accelerate convergence in income levels across countries.

Using data on two measures of human capital, taken from Penn World Table 10 and the latest version of Barro and Lee (2013), we start by analyzing convergence in human capital and whether it preceded convergence in income levels. Our first measure of convergence is $\sigma-$convergence. We say there is $\sigma-$convergence if there is a tendency for the cross-sectional dispersion to decline over time. Dispersion is measured by the variance across countries of the log of human capital. We find that the variance of human capital started to decline a long time before the fall in the variance of income per capita. In a broad sample of countries, the evidence shows that $\sigma-$convergence in human capital started around 1977. Meanwhile, divergence in per capita income between countries was the dominant force until the 1990s. It was only around 2000 when the variance of the log of per capita GDP started to decline. We compute which part of the variance in per capita GDP is determined by the variance of human capital. From 1970 onwards, the contribution of human capital to the variance of per capita income stabilizes at around 17.0 per cent.

Most of the literature on convergence mainly focuses on $\beta-$convergence, that is, a negative correlation between the initial level of a variable and its subsequent growth rates. We estimate the relationship between the human capital index in period t and its growth rate over the next 10 years from 1960 to 2020. We find that $\beta-$convergence in human capital has been statistically significant from the 1980s onwards, in line with the evolution of $\sigma-$convergence.[2] Unconditional to other factors, countries that started with lower levels of human capital experienced higher growth rates in education. The

[2] Barro and Sala-i-Martin (1992) and Young et al. (2008) show that $\beta-$convergence is a necessary, but not a sufficient condition for $\sigma-$convergence.

coefficient of $\beta-$convergence in human capital increases over the years, suggesting a greater convergence process over time. Absolute convergence in human capital has been driven by a slowdown in the growth rates of human capital in the regions at the top (advanced countries and Europe and Central Asian regions), a speeding-up of the growth rates of the regions at the bottom (South-Asia, Sub-Saharan Africa, the Middle East, and North Africa), and a plateauing of the regions in the middle (Latin America and the Caribbean).

As human capital is one of the main determinants of income per capita, the convergence in human capital, starting about 1980, might have played a role in the absolute convergence in per capita income observed in recent decades. As a first step, we corroborate in our dataset the findings in the literature regarding the convergence in income levels. In line with previous studies, we find an absence of absolute convergence in per capita income over a long period of time (Baumol, 1986; Barro, 1991; Pritchett, 1997 and Rodrik, 2013) and a change in the slope from the 2000s (as Kremer et al., 2021). Then, we use the omitted variable formula to analyze the role of human capital in this process. We decompose absolute convergence in two parts: the contribution of conditional convergence and the contribution of human capital. The difference between absolute convergence (β) and convergence conditional to human capital (β^*) is the contribution of human capital. If human capital did not play a role in absolute convergence, we would expect absolute convergence to be equal to conditional convergence ($\beta = \beta^*$).

Our results show that human capital is highly and statistically significant related to the subsequent growth rates in per capita income and is also highly related to the initial level of income. For the period for which there is absolute convergence, 2000s and 2010s, we find that convergence, conditional to the initial level of human capital, is twice as large as absolute convergence. For example, for the decade of 2000s, the coefficient of absolute convergence is -0.575 and that of convergence conditional to human capital is -1.359. Conditioned on human capital, the convergence coefficient increases by 0.784 points.

We show the results are robust to a variety of sensitivity tests. First, Johnson et al. (2013) show that growth rates can vary substantially across datasets. We check whether the results are sensitive to measuring income with the World Development Indicators (WDI). When we use the alternative measure of GDP, the difference between absolute convergence and convergence conditional to human capital increases.

Second, it could be possible that human capital is picking up the role of other determinants of the steady state in the convergence process. One of the most important determinants of the differences in growth rates between countries are institutions. To analyze the role of this determinant, we check the difference between absolute convergence and convergence conditional to institutions, measured by the democracy index, as in Acemoglu et al. (2019), and by the Political Rights Index. Unlike the results with human capital, when we control for institutions, the coefficient of absolute convergence is almost equal to the coefficient of conditional convergence, suggesting that institutions have played a small role in explaining absolute convergence in recent decades.

Third, we test whether the results are driven by the omission of relevant determinants of the growth rates that are constant over time and specific to each country. Acemoglu and Molina (2021) argue that Kremer et al. (2021) findings could be biased due to the omission of country fixed effects that account for unobserved determinants of per capita GDP across countries. The omission of unobserved heterogeneity could bias the convergence coefficients towards zero.[3]

We check the robustness of the results to the estimation of a model that accounts for unobservable heterogeneity. According to the results in the literature, once we control for fixed effects, the convergence coefficient increases and is statistically significant in all decades. The findings also reveal that even controlling for fixed effects, the coefficient of convergence increases when we condition on human capital. The increase in the convergence coefficient is much higher when we condition on human capital than when we condition on institutions.

However, fixed-effect estimators can cause an upward bias in convergence rates in dynamic models with moderate time dimension (Nerlove, 2000). The large increment in the convergence coefficient found with the fixed effect estimator might be due to both the increase in convergence, once we condition for time-invariant determinants of long-run growth, and the upward bias of the fixed effect estimator in a dynamic model. As Barro (2015) shows, there is a trade-off between the omitted variable bias in the OLS model and the upward bias in the fixed-effect estimator.

An alternative approach to control for unobserved heterogeneity, suggested by Temple (1998), is to proxy initial efficiency by controlling for regional dummies. The idea is that the differences in initial efficiency are much greater between regional groups of countries than within regions. When we control for regional dummies the results hold. Again, the convergence coefficient increases when we condition on human capital measures, and

[3] The relevance of controlling for country fixed effects in convergence equations was already pointed out by Islam (1995) and Caselli et al. (1996). Islam (2003) and Durlauf et al. (2005) offer an excellent survey of the literature.

the increment is greater than when we condition on institutions.

Most of the literature on convergence has concentrated on convergence in income levels. Our paper adds to the literature by analyzing the role of human capital in this process. Initially, the focus was on absolute convergence in income levels. In a pioneering paper, Baumol (1986) uses data on Madison (1982) for the period 1870-1979 and finds absolute convergence in output per labor among 16 industrialized nations but finds no evidence of convergence in GDP per capita in a broader sample of 72 countries from 1950 to 1980. De Long (1988) showed that Baumol's finding on absolute convergence for industrialized countries is driven by selection bias and measurement error in the independent variable.[4] Once both considerations are taken into account, absolute convergence is absent even in the set of rich economies. In a broader sample of 98 countries, Barro (1991) confirms this finding and shows that per capita growth rates are not correlated with the starting levels of GDP per capita during the period 1960-1985. Pritchett (1997) found that convergence between the poorest and the richest economies did not occur between 1870 and 1990, suggesting that there has been divergence for long-time horizons.[5]

Instead of absolute convergence, for many years the literature focused on conditional convergence, in the sense that poor countries converge to their steady states after conditioning on institutions, policies or other country-specific factors. Barro and Sala-i-Martin (1992) and Mankiw, Romer and Weil (1992) were among the first to show that conditioning on variables that proxy for determinants of the steady state renders a negative and statistical significant coefficient of initial income on growth in a broad sample of countries. Absolute or unconditional convergence has been found only in countries or regions that share similar long-run characteristics or steady-state determinants (see Barro and Sala-i-Martin, 1992), but not in a broad sample of countries (Barro, 1991, Pritchett, 1997, or Rodrik, 2013).

The lack of evidence has rendered a rejection of the absolute convergence hypothesis during several decades.[6] Nevertheless, the new evidence by Kremer et al. (2021) and Patel et al. (2021) shows some signals of unconditional convergence in per capita income in recent decades. In this paper we show that convergence in human capital has played an important role in the recent convergence in income levels observed in the data.

[4] Baumol´s sample is criticized as being an ex post sample of countries that have converged. Countries that were relatively rich in 1870 but did not converge, such as Chile, Argentina, Spain, and Portugal, were not included in the sample of the 16 industrialized nations.

[5] More recently, Rodrik (2013) shows strong unconditional convergence in labor productivity in manufacturing, but an absence of absolute convergence in per capita GDP in a broad sample of countries.

[6] Johnson and Papageorgiou (2020) present and excellent survey of the literature.

Evidence on the relationship between human capital convergence and income convergence has been scarce in the literature. Using data for 84 countries for the period 1970-1990, Sab and Smith (2002) find convergence in human capital, measured with indicators that include both education and health. The paper, however, does not analyze whether convergence in human capital relates to convergence in income levels.

In a pioneering paper, O´Neill (1995) found that, between 1967 and 1985, human capital convergence explained income convergence among developed countries. However, despite the convergence in educational levels, the increase in the skill premium led to divergence in income levels in the least developed countries and in the world as a whole. Our paper focuses on a more recent period and uses a measure of human capital that takes into account not only the years of schooling but also the return of each level of education. For the years 2000-2020, for which absolute convergence has been found, we show that convergence in human capital has indeed helped to explain convergence in income levels in a broad sample of countries with different levels of development.

The structure of the paper is as follows. Section 2 analyzes σ-convergence in human capital and in per capita income and checks to what extent the variance in human capital explains the variance in per capita income. Section 3 presents the results of β-convergence in human capital, and analyzes the role of human capital in the process of absolute convergence in per capita income found in the recent decades. Section 4 analyzes the robustness of the results. Finally, Section 5 concludes.

2. $\sigma-$convergence

In this paper, we rely on two basic data sources. Most of the data, as GDP and population, is taken from Penn World Table 10 (see Feenstra, Inklaar and Timmer, 2015). Since PWT version 8, this data set also includes an estimate measure of human capital (h_{PWT}) for a large sample of countries, which is based on the approach proposed by Hall and Jones (1999) and Caselli (2005).

$$h_{PWT} = e^{\phi(s)} \tag{1}$$

where s is the average years of education of the population 15-64 years old, and $\phi(s)$ is a linear function that aggregates the years of schooling for primary, secondary, and tertiary education. In particular, $\phi(s) = 0.134s$ if $s \leqslant 4$, $\phi(s) = 0.134s + 0.101(s-4)$ if $4 < s \leqslant 8$, and $\phi(s) = 0.134s + 0.101s + 0.068(s-8)$ if $s > 8$ The coefficients $\phi(s)$ are taken from Psacharopoulos (1994) and correspond to the rates of return of an additional year of education for the three levels of education considered.

PWT combines two data sets for years of schooling. For 95 countries, years of schooling are based on Barro and Lee (2013) data (BL henceforth). For 55 countries, data are based on Cohen and Leker (2014) estimates (CL henceforth). As shown by De la Fuente and Doménech (2006) and Cohen and Soto (2007), the Barro and Lee (2013) estimates are rather noisy and are subject to some breaks over time and measurement errors. In PWT the choice of the data source depends on which series is closer to De la Fuente and Domenech (2006) or the UNESCO data, if a series for a country shows a decline in the average year of schooling, or if data start in 1950 versus 1960. The BL data are available every five years from 1950 to 2015, whereas the CL data are available every 10 years, from 1960 to 2010, but include projections to 2020. PWT interpolates linearly between observations, and extrapolates BL data to 2019 using the growth rates of CL, if they are available, or, alternatively, the trend growth of BL from 2005 to 2015.

For comparisons, we follow the same approach as in PWT to estimate h_{BL} using only the original Barro and Lee (2013) data. The correlation between h_{PWT} and h_{BL} in log. levels is 0.96, but falls to 0.65 in rates of growth.

As we need to combine human capital with other variables in PWT, the sample of countries with available data changes over time. Thus, we have 55 countries with complete information from 1950 to 1969, 99 from 1960 to 1969, 124 from 1970 to 1989, and 140 from 1990 to 2019.

Figure 1 shows the variance of the log of h_{BL} for the different samples of countries that start in different decades. As we can observe, the evolution over time is very similar for all samples, with the exception of the sample of 55 countries starting in 1950, where the convergence process has been more intense from late 1970s onwards. Given these similarities, we can extrapolate backwards the variance of $\ln h_{BL}$ for the whole sample of countries from 1950 to 2015, using the rate of change of the variance of the smaller samples of countries. Figure 1 shows that this variance has been decreasing from 1977 onward.

Figure 2 shows the variance of the log of h_{PWT}, for the same samples of countries. Again, the evolution over time is highly analogous for all samples, except for the sample of 55 countries. The main differences with respect to $\ln h_{BL}$ are that the level of the variance of $\ln h_{PWT}$ is slighter greater and the convergence process is not as intense as with the BL data.

[6] We rely on years of schooling since this variable is available for more countries and years than quality indicators of human capital, as discussed by De la Fuente and Domenech (2022).

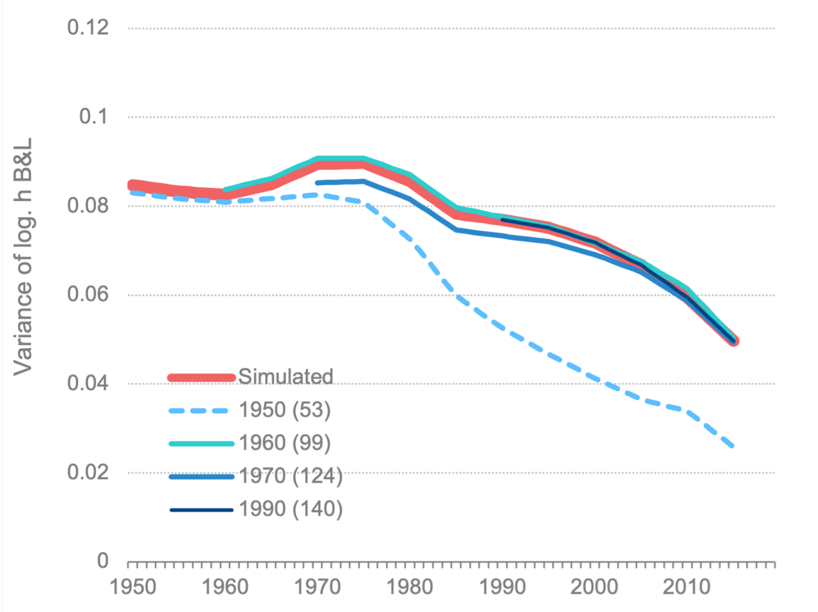

Figure 1: *Variance of* h_{BL} *in logs.*

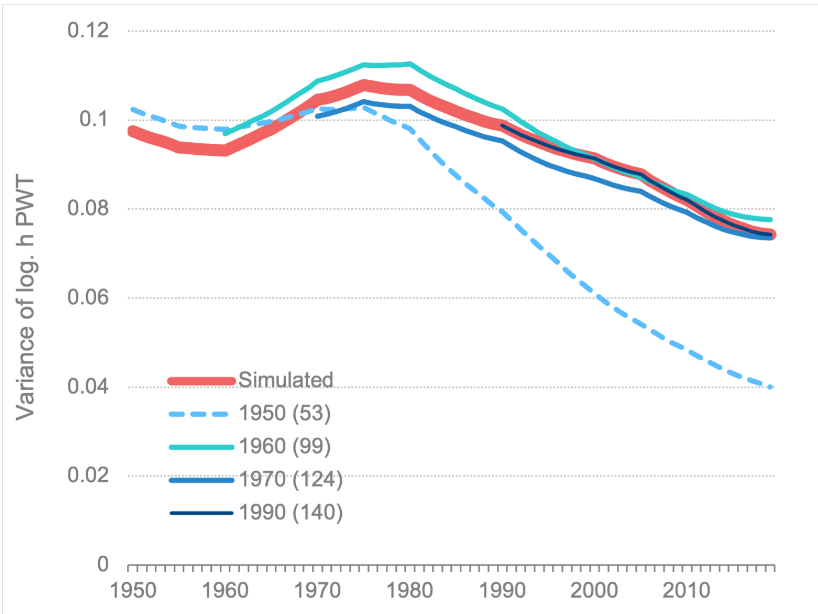

Figure 2: *Variance of* h_{PWT} *in logs.*

As human capital is one of the main determinants of income per capita, the convergence process shown in Figures 1 and 2 suggests the convenience of testing its effects on the convergence of GDP per capita (y). In this section we analyse the success of the variance of $\ln h_{PWT}$ and h_{BL} in explaining the variance of ($\ln y$) across countries, whereas in the next section we test the relevance of both indicators of human capital in terms of the β-convergence hypothesis.

For simplicity, we assume that GDP per capita for country i and time t can be expressed in terms of the following Cobb-Douglas function

$$y_{it} = A_{it} k_{it}^{\alpha} h_{it}^{1-\alpha} \tag{2}$$

where A is total factor productivity (TFP) and k the capital to labor ratio. As in Klenow and Rodriguez-Clare (1997) and Hall and Jones (1999), we can rearrange terms and write the production function in terms of the capital-to-output ratio:

$$y_{it} = h_{it} A_{it}^{\frac{1}{1-\alpha}} \left(k_{it}/y_{it}\right)^{\frac{\alpha}{1-\alpha}} \tag{3}$$

Defining the term $A_{it}^{\frac{1}{1-\alpha}} \left(k_{it}/y_{it}\right)^{\frac{\alpha}{1-\alpha}}$ as y_{AKY}, then we have:

$$\text{var}(\ln y_t) = \text{var}(\ln h_t) + \text{var}(\ln y_{AKYt}) + 2\text{cov}(\ln y_{AKYt}, \ln h_t) \tag{4}$$

Taking into account that σ-convergence refers to the evolution over time of the standard deviation of the log of GDP per capita across countries (see Barro and Sala-i Martin 1992), equation (4) shows the contribution of the convergence of human capital to convergence of income, measured in terms of its variance instead of the standard deviation.

As in the case of $\ln h_{PWT}$ and $\ln h_{BL}$, we begin analysing the sensitivity of the variance of the log of GDP per capita to changes in the sample of countries.[7] As we can see in Figure 3, the composition of countries in the four different samples affects the level of the variances, although not so much their time profiles. As in the case of human capital, we extrapolate backward the variance of $\ln y$ for the entire sample of countries from 1950 to 2015, using the variance of the smaller sample of countries.

As noted by Kremer et al. (2021), Figure 3 shows that divergence between countries was the dominant force until the 1990s. In their research, they use an unbalanced panel with all countries with data on GDP per capita available. This approach intensifies divergence until 1970. In our case, the backward extrapolation of the variance with the larger

[7] GDP per capita is measured using PWT variable RGDPNA.

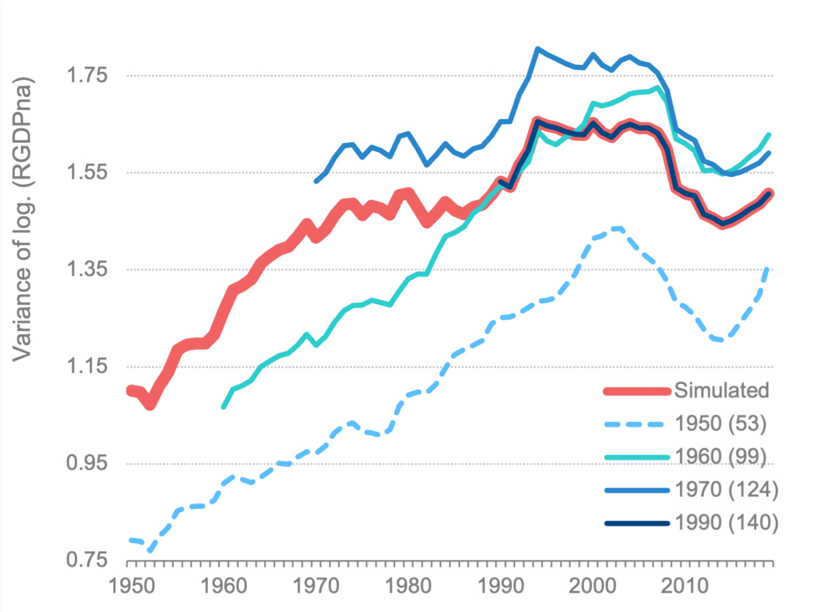

Figure 3: *Variance of GDP per capita in logs.*

sample of 140 countries, using the rate of change of smaller samples, makes divergence less pronounced. The Great Recession marked the start of a process of convergence for eight years until 2016 that is common for the four different samples of countries, partially reverted in the last three years of the sample.

Now we calculate which part of the variance of $\ln y$ is determined by the variance of human capital. To this end, we use h_{PWT} as a measure of human capital and compute two ratios. The first is a strict measure of its contribution, given by the ratio of the variance of human capital to the variance of GDP per capita:

$$Contribution_1 = \frac{\text{var}(\ln h_{PWT})}{\text{var}(\ln y)}, \tag{5}$$

whereas the second measure also includes the covariance between human capital and the rest of the determinants of GDP per capita in equation (3), that is, the stock of physical capital and TFP.

$$Contribution_2 = \frac{\text{var}(\ln h_{PWT}) + \text{cov}(\ln h_{PWT}; \ln y_{AKY})}{\text{var}(\ln y)} \tag{6}$$

In Figure 4 we represent both measures of the contribution of human capital to the variance of the log of GDP per capita. The breaks in 1960, 1970 and 1990 are due to the changes in the samples from 53 to 99, 124 and 140 countries, respectively. We can see that

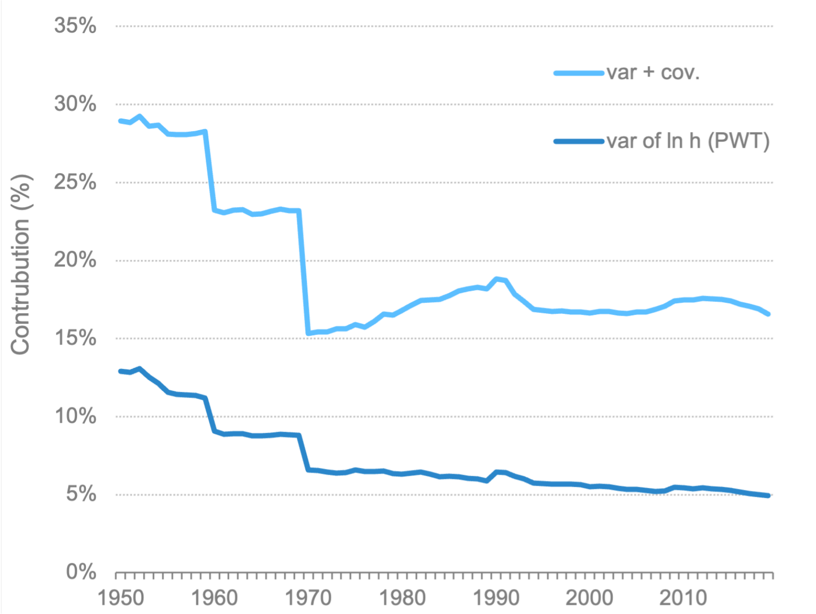

Figure 4: *Contribution of human capital to the variance of the log of income per capita*

in the case of the sample of 53 countries in the 1950s, human capital contributes around 12 percent to the variance of per capita income.

As expected, the covariance between human capital and $\ln y_{AKY}$ is positive, thus helping to increase the contribution of human capital to the variance of per capita income to around 28.5 per cent in the 1950s. As we increase the number of countries from 53 to 99 in the 1960s and to 124 in the 1970s, we observe a significant reduction in the contribution of human capital. Therefore, the composition of the sample of countries is very relevant in order to determine the contribution of different production factors to GDP per capita. From 1970 onward, the contribution of human capital stabilizes at around 17.0 per cent, according to the second measure that includes the covariance component.[8]

3. $\beta-$convergence

As is well known, there is β-convergence across countries when the growth rate of a variable is inversely related to its initial value. As preliminary evidence, Figure 5 shows the relationship between the PWT human capital index in the period t and its growth

[8] As a robustness test, we have computed the contribution of human capital to the variance of the log of GDP per capita using PWT variable RGDPo instead of RGDPNA. The contribution increases slightly in the 1950s to 29.3 per cent, and stabilizes at around 18.2 per cent from 1970 onwards.

rate over the next 10 years $t, t+10$. There is $\beta-$convergence when the slope of this relationship is negative and statistically significant. With the exception of the 1960s and the 1970s, the figure shows a clear negative slope in all decades. Countries that start with lower levels of education in the base year tend to growth faster over the subsequent decade, suggesting that there has been human capital convergence over a long time horizon. Although $\beta-$convergence is not a sufficient condition for $\sigma-$convergence (see Barro and Sala-i-Martin, 1992, 227-8), the evidence presented in Figure 5 is consistent with the convergence process in Figure 2 from 1980 onward.

Table 1 analyzes this evidence by testing the statistical significance of the slopes in Figure 5. The dependent variable is the average growth rate of human capital over each decade in the sample. The explanatory variables include human capital at the beginning of each decade and dummy variables that control for time effects. We display the results for the human capital index in PWT, $\ln h_{PWT}$, and the human capital index computed with the average years of schooling from Barro and Lee (2013), $\ln h_{BL}$.

Columns (1) and (3) show the result for the whole period.[9] The pooled OLS regression model shows a strong correlation between the initial level of human capital and its growth rate. The coefficient of the initial human capital is negative and statistically significant at the 1 per cent level for both measures of human capital. In columns (2) and (4) we include interaction terms between the level of human capital at the beginning of each period and a year dummy (y_t) to analyze how convergence has changed over time. This specification provides the same results as estimating cross-section regressions individually for each decade. Convergence in human capital starts around 1980 for the PWT variable and in 1970 for Barro and Lee. The coefficients of the interaction terms are statistically significant at the 1 per cent level from 1980 onward for $\ln h_{PWT}$ (column (2)) and from 1970 onward for $\ln h_{BL}$ (column (4)). The evidence also shows increasing coefficients over the years, suggesting a greater convergence process over time.

The convergence in human capital could have occurred because countries that started with high levels of human capital have seen their growth rates slow, because countries with low initial levels have seen their growth rates increase, or both. Table 2 shows the average rate of human capital growth in each decade for seven geographical regions with different initial levels of human capital. [10]

[9] Barro and Lee´s (2013) data is available up to 2015. For the decade 2010-2020, the average growth rate of h_{BL} is calculated from 2010 to 2015.

[10] In Table 2 we use the human capital index computed with Barro and Lee's (2013) data because it is a balanced panel with 140 countries from 1960 to 2015.

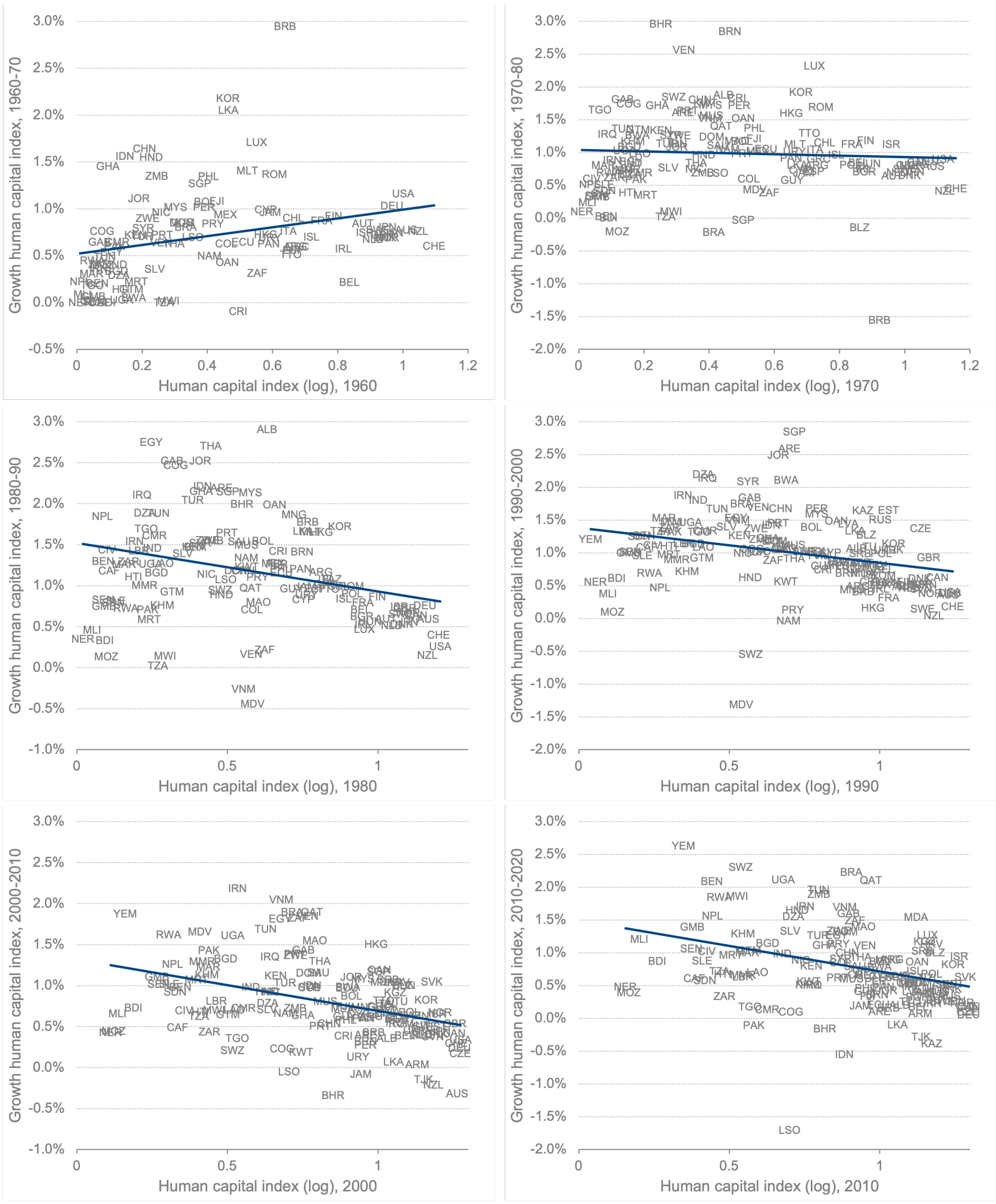

Figure 5: *$\beta-$convergence in human capital (PWT)*

Table 1: $\beta-$convergence in human capital, 1960-2020

	(1)	(2)	(3)	(4)
	Dep. variable: decadal average human capital growth rate			
	h_{PWT}		h_{BL}	
$\ln h$	-0.390***		-0.588***	
	(0.062)		(0.081)	
$\ln h \times y_{1960}$		0.474***		0.124
		(0.123)		(0.191)
$\ln h \times y_{1970}$		-0.105		-0.356**
		(0.166)		(0.179)
$\ln h \times y_{1980}$		-0.590***		-0.796***
		(0.165)		(0.187)
$\ln h \times y_{1990}$		-0.536***		-0.532***
		(0.133)		(0.164)
$\ln h \times y_{2000}$		-0.628***		-1.090***
		(0.126)		(0.146)
$\ln h \times y_{2010}$		-0.780***		-2.015***
		(0.202)		(0.416)
Constant	0.689***	0.489***	0.845***	0.614***
	(0.072)	(0.067)	(0.054)	(0.040)
Obs.	821	821	980	980
R^2	0.122	0.155	0.137	0.208
Year FE	yes	yes	yes	yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

In 1960, the highest level of human capital was concentrated in advanced economies, followed by Europe and Central Asia. Latin America and the Caribbean countries came third, followed by the countries in East Asia and the Pacific region. At the bottom were countries in Middle East and North Africa, South Asia, and Sub-Saharan Africa, respectively. During this decade there was a slowdown in the growth rates of human capital in advanced economies and a speeding-up in the growth rates in East Asia and the Pacific region. However, there was no convergence at the bottom. South Asia and Sub-Saharan African countries had the lowest initial levels of human capital and also show the lowest growth rates.

From 1970 onward, advanced economies, which were ranked as the region with the highest initial levels of human capital, show the lowest growth rates across almost all

Table 2: Decadal Average Human Capital Growth Rate by Geographical Region

			Growth Rate						Ranking						
	Countries	HC_{1960}	1960s	1970s	1980s	1990s	2000s	2010s	HC1960	1960s	1970s	1980s	1990s	2000s	2010s
Whole sample	140	1.642	1.031	1.222	1.072	0.875	0.832	0.779							
Advanced Economies	24	2.226	0.923	1.021	0.681	0.651	0.635	0.258	1	5	6	7	7	6	7
East Asia and the Pacific	17	1.509	1.387	1.423	1.008	0.967	1.129	0.621	4	1	2	5	3	2	5
Europe and Central Asia	20	2.078	1.191	1.330	0.809	0.765	0.450	0.305	2	2	3	6	6	7	6
Latin America and the Caribbean	24	1.629	1.036	1.179	1.139	0.928	0.763	0.670	3	4	4	4	4	5	4
Middle East and North Africa	17	1.370	1.179	1.544	1.612	1.184	0.951	1.341	6	3	1	1	2	4	2
South Asia	6	1.309	0.910	0.821	1.176	1.199	1.232	1.463	6	6	7	3	1	1	1
Sub-Saharan Africa	32	1.217	0.764	1.134	1.206	0.798	0.975	1.203	7	7	5	2	5	3	3

decades, while regions at the bottom start speeding up. Sub-Saharan African countries jump from the 7th position in the 1960s to the 3rd position in the 2000s, and countries in the Middle East and North Africa show one of the highest growth rates over the years.

Countries in South Asia deliver one of the most striking performances. Whereas this region had the lowest growth rates in the 1970s, it jumps up to third position in the 1980s, and from the 1990s onward, South Asia is the region with the highest growth rates during three decades. Meanwhile, there is hardly any movement in the middle of the distribution. Countries in the Latin America and Caribbean region hold a fourth position in terms of growth rates in almost all decades.

Overall, this evidence indicates that $\beta-$convergence in human capital started mainly around 1980. Convergence in human capital has been driven by a slowdown in the growth rates of regions at the top, a speeding-up of the growth rates of the regions at the bottom, and a plateauing of regions in the middle.

3..1 Human capital and $\beta-$convergence in GDP per capita

Has convergence in human capital played a role in the process of convergence in per capita GDP observed in recent decades? To answer this question, we estimate three equations. Firstly, we analyze the relationship between initial income and growth using the following empirical framework:

$$\ln(y_{i,t+\triangle t}) - \ln(y_{i,t}) = \alpha + \beta_t \ln(y_{i,t}) + \mu_t + \epsilon_{i,t} \tag{7}$$

where y is the real GDP per capita in the country i in year t,[11] μ_t is a year fixed effect that controls for shocks that are common to all countries, and $\epsilon_{i,t}$ is an error term that varies across countries and years. We assume that $\epsilon_{i,t}$ is uncorrelated with the explanatory variables. The convergence coefficient β is allowed to vary over time. In this framework, the estimate of β will be a measure of unconditional or absolute convergence. There is unconditional convergence in GDP per capita if $\beta < 0$.

Then, we analyze whether the relationship between initial income and growth changes conditioning on initial human capital. To do so, we include a measure of human capital in the set of controls:

$$\ln(y_{i,t+\triangle t}) - \ln(y_{i,t}) = \alpha + \beta_t^* \ln(y_{i,t}) + \lambda_t \ln h_{i,t} + \mu_t + \varepsilon_{i,t} \tag{8}$$

[11] The variable is the real GDP per capita at constant 2017 national prices (in million 2017 USD) from the PWT10. In the following section we analyze the robustness of the results with alternative measures of GDP.

where $lnh_{i,t}$ is the measure of human capital in the country i at the beginning of the period. The effect of human capital on GDP per capita growth, λ_t, is allowed to vary over time. In this expression, the coefficient β^* captures convergence conditional to controlling for the initial level of human capital. There will be conditional convergence if $\beta^* < 0$.

If we assume that human capital is a determinant of GDP per capita growth and we omit this variable in the set of controls, we can decompose the difference between absolute and conditional convergence through the omitted variable bias formula. An omitted variable bias exists if human capital is a determinant of economic growth and if it is correlated with $\ln y$. If human capital and GDP per capita are correlated as follows:

$$\ln h_{i,t} = \phi + \delta_t \ln(y_{i,t}) + \mu_t + v_{it} \tag{9}$$

then, we can substitute (9) into (8) and we can decompose absolute convergence (β_t) as the contribution of conditional convergence (β_t^*) and the contribution of human capital, measured by the product of the effect of human capital on growth (λ_t) and the coefficient of GDP per capita (δ_t) in equation (9):

$$\beta_t = \beta_t^* + \lambda_t \times \delta_t \tag{10}$$

If human capital did not play any role in absolute convergence, we would expect $\lambda_t \times \delta_t = 0$ and $\beta_t = \beta_t^*$. If human capital affects convergence and $\lambda > 0$ and $\delta > 0$, absolute convergence will occur if $\beta^* < 0$ and $\beta^* > (\lambda \times \delta)$.

Table 3 displays the results of estimating equations (7)-(9). Equation (7) assumes that initial conditions, apart from initial income, do not matter for growth. In line with the findings in the literature, the results in column (1) corroborate the absence of absolute convergence from 1960 to 2000 (Barro, 1991; Pritchett, 1997; or Rodrik, 2013), and a change in the slope thereafter (Kremer et al., 2021). For the period 2000-2010, the estimated coefficient of β is negative and statistically significant at the one percent level, suggesting that a process of absolute convergence might have started from the 2000s onward. Independently of initial conditions, countries that started with lower GDP per capita in the year 2000, experienced more rapid growth rates over the subsequent decade. Results also display a negative estimate of β for the period 2010-2019, though the coefficient is not statistically significant at the standard levels.

We check whether the results are driven by atypical observations. In column (2) we include dummies that control for outliers.[12] Whereas controlling for outliers hardly

[12] We include dummies for those countries and years for which the residuals are three times higher than their

Table 3: Conditional and unconditional $\beta-$convergence

	Decadal Average Human Capital Growth Rate							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			h_{PWT}			h_{BL}		
	β	β	β^*	λ	δ	β^*	λ	δ
1960s	0.336[c]	0.336[c]	-0.653[a]	4.283[a]	0.231[a]	-0.580[c]	4.392[a]	0.208[a]
	(0.183)	(0.183)	(0.346)	(1.212)	(0.021)	(0.312)	(1.210)	(0.019)
1970s	0.030	0.236	-0.215	2.717[a]	0.171[a]	-0.281	3.427[a]	0.155[a]
	(0.264)	(0.189)	(0.252)	(0.954)	(0.026)	(0.242)	(1.009)	(0.022)
1980s	-0.203	-0.252	-1.232[a]	5.841[a]	0.173[a]	-1.201[a]	6.489[a]	0.151[a]
	(0.248)	(0.245)	(0.293)	(0.953)	(0.021)	(0.283)	(1.089)	(0.019)
1990s	0.114	0.014	-0.012	0.134	0.195[a]	0.063	-0.293	0.171[a]
	(0.206)	(0.175)	(0.268)	(0.988)	(0.015)	(0.251)	(1.159)	(0.014)
2000s	-0.575[a]	-0.575[a]	-1.359[a]	4.203[a]	0.174[a]	-1.190[a]	4.013[a]	0.153[a]
	(0.164)	(0.166)	(0.241)	(0.866)	(0.015)	(0.258)	(1.039)	(0.014)
2010s	-0.173	-0.440[a]	-0.904[a]	2.454[a]	0.183[a]	-0.965[a]	3.275[a]	0.155[a]
	(0.238)	(0.142)	(0.195)	(0.845)	(0.015)	(0.187)	(0.974)	(0.013)
Constant	2.366[a]	2.366[a]	2.366[a]	2.366[a]	0.513[a]	2.366[a]	2.366[a]	0.504[a]
	(0.273)	(0.275)	(0.277)	(0.277)	(0.044)	(0.277)	(0.277)	(0.040)
R^2	0.101	0.313	0.403	0.403	0.621	0.397	0.397	0.643
Obs	821	821	821	821	821	821	821	821
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Dummy outliers	NO	YES	YES	YES	YES	YES	YES	YES

a, b and c denote statistically significant coefficients at 1, 5 and 10 per cent probabilities, respectively.

changes the results in most of the decades, the coefficient of β convergence increases and becomes statistically significant for the years 2010-2019.[13] Thus, in line with the literature, the results suggest an absence of absolute convergence before the year 2000, and evidence of convergence afterwards.

How do the results change when we condition for the initial level of human capital? The results in column (3) show that the coefficient of β^*-convergence is negative in all periods, although it is not statistically significant in all decades. Column (4) shows that the initial level of human capital is an important determinant of growth rates. With the exception of the 1990s, human capital has a positive effect on subsequent growth rates. In all periods λ_t is positive and statistically significant at the 1 percent level. Human capital is also highly related to the initial level of income. The estimates of δ are positive and

standard deviation. The dummies include Botswana (1970), Cambodia (1970), Kuwait (1970), Liberia 1980), Moldova (1990), Tajikistan (1990), Ukraine (1990), D.R. of the Congo (1990), Sierra Leone (1990), Venezuela (2010) and Yemen (2010).

[13] Venezuela is a clear outlier for the years 2010-2019, with the lowest GDP per capita in 2010, and a growth rate of -11.16 percent during this period.

Table 4: Decomposition of $\beta-$convergence

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		HC PWT			*HC BL*		
	β	β^*	$(\lambda \times \delta)$	$\beta^* + (\lambda \times \delta)$	β^*	$(\lambda \times \delta)$	$\beta^* + (\lambda \times \delta)$
2000s	-0.575	-1.359	0.731	-0.628	-1.190	0.614	-0.576
2010s	-0.440	-0.904	0.449	-0.455	-0.965	0.508	-0.457

statistically significant at 1 per cent level in almost all periods (column (5)). The results are similar to the measure of human capital computed with Barro and Lee's (2013) data (column (6)-(8)). It is worth noting that λ is above 2 and statistically significant in all decades, except in the 1990s. Meanwhile, δ is around 0.18 and statistically significant in all decades.

Table 4 summarizes the decomposition of absolute β-convergence into conditional convergence and the role of human capital, in the two decades in which we observe absolute convergence, that is, from 2000 onward. Columns (1) and (2) show that conditional convergence is twice as large as absolute convergence. The difference between absolute and conditional convergence ($\beta - \beta^*$) is the role of human capital ($\lambda \times \delta$). For the period 2000-2010, the coefficient of absolute convergence (β = -0.575) more than doubles once we condition for human capital (β^* = -1.359), suggesting that human capital accelerates the process of income convergence across countries during that period. In quantitative terms, the role of human capital in the convergence process is the difference between both coefficients ($\beta - \beta^*$ = 0.784). Once human capital is controlled for, the convergence coefficient also doubles for the period 2010-2019. Results hold when we measure human capital with Barro and Lee's (2013) measures. In what follows, we check the robustness of these findings.

4. Robustness

4..1 Alternative measures of GDP

In this paper we measure income levels with data from Penn World Tables, which is the most widely used source of comparable data on GDP for a broad number of countries and periods. The variable we use is the Real GDP per capita at constant 2017 national prices (in million 2017 USD) from PWT10. Johnson et al. (2013) show that the estimates of GDP might vary substantially across versions of the Penn World Tables. When they analyze the

Table 5: Unconditional and conditional $\beta-$convergence using WDI GDP

	Alternative measure of GDP (World Development Indicators)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			HC PWT			*HC BL*		
	β	β	β^*	λ	δ	β^*	λ	δ
1960s	0.551[a]	0.551[a]	0.123	2.209	0.194[a]	0.069	2.840	0.170[a]
	(0.146)	(0.150)	(0.386)	(1.872)	(0.017)	(0.333)	(1.856)	(0.015)
1970s	0.149	0.216	-0.320	2.864[c]	0.187[a]	-0.380	3.566[b]	0.167[a]
	(0.144)	(0.132)	(0.318)	(1.486)	(0.015)	(0.284)	(1.454)	(0.014)
1980s	0.086	0.165	-0.887[a]	5.719[a]	0.185[a]	-0.851[a]	6.213[a]	0.161[a]
	(0.200)	(0.191)	(0.327)	(1.274)	(0.013)	(0.310)	(1.436)	(0.012)
1990s	0.281[c]	0.213	0.016	1.185	0.164[a]	0.033	1.252	0.141[a]
	(0.153)	(0.130)	(0.270)	(1.296)	(0.011)	(0.246)	(1.393)	(0.011)
2000s	-0.464[a]	-0.424[a]	-1.219[a]	5.124[a]	0.149[a]	-1.188[a]	5.590[a]	0.131[a]
	(0.133)	(0.120)	(0.165)	(0.742)	(0.010)	(0.158)	(0.835)	(0.010)
2010s	-0.372[a]	-0.308[a]	-0.942[a]	3.792[a]	0.150[a]	-0.927[a]	4.373[a]	0.127[a]
	(0.119)	(0.102)	(0.198)	(0.952)	(0.011)	(0.184)	(1.066)	(0.010)
Constant	-1.283	-1.283	1.120	1.120	-1.087[a]	1.232	1.232	-0.885[a]
	(1.160)	(1.169)	(2.226)	(2.226)	(0.132)	(1.857)	(1.857)	(0.118)
R^2	0.138	0.313	0.381	0.381	0.719	0.374	0.374	0.728
Obs	664	664	664	664	664	664	664	664
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Dummy outliers	NO	YES	YES	YES	YES	YES	YES	YES

robustness of the results of relevant papers in the growth literature across datasets, they find that studies that use long-run growth rates (30-year averages) are robust across PWT versions, whereas results based on annual data are not. We check whether our findings, based on growth rates over a 10-year span, hold with different measures of GDP.

Table 5 displays the results of estimating equations (7)-(9) with the measure of GDP per capita from the World Development Indicators (WDI). Results hold. In line with previous findings, the measure of GDP from the WDI also shows absolute convergence in GDP per capita from the 2000s onward. When we control for human capital, the coefficient of conditional convergence triples during the 2000s and 2010s, suggesting that human capital played a relevant role in the convergence process.

[13] Data are in constant 2015 prices, expressed in U.S. dollars.

4..2 Alternative controls

Conditional on determinants of the steady state, several papers have found evidence of conditional convergence (Barro and Sala-i-Martin, 1992; Mankiw, Romer and Weil, 1992). Although human capital is one of the main determinants of long-term growth rates, it has been argued that institutions are the fundamental cause of economic growth and the main reason for differences in economic development between countries (Acemoglu et al., 2005).

There has been much discussion about whether it is necessary first to increase the human capital of a society in order to improve the quality of its institutions , or whether the causality goes in the opposite direction, that is, whether the influence of institutional quality on well-being is due to the fact that it increases the incentive to devote resources and personal effort to the accumulation of knowledge. Glaeser et al. (2004), based on the work of Lipset (1960), consider that the causality goes from human capital to institutional quality. Conversely, Acemoglu et al. (2014) argue that the causality moves in the opposite direction, giving as an example the case of the first European settlers, for whom their low educational level did not suppose a significant limitation in the subsequent development of more advanced institutions in the colonies. In general, both determinants interact in a complementary and dynamic way and are able to generate a virtuous circle. Good institutions are essential to harness all the human capital that a society accumulates. In the same way, it is much easier for institutions to function better if society has the necessary human capital to do so.

Since in our analysis of conditional convergence we have only controlled for human capital, it could be possible that the role of human capital on the process of convergence is picking up the effect of institutions. To analyze this possibility, we compare the difference between absolute and conditional convergence $(\beta - \beta^*)$ when we condition on human capital and when we alternatively control for institutions.

We measure institutions with two standard variables in the empirical growth literature. The first one is the dichotomous measure of democracy computed by Acemoglu et al. (2020). This variable is available annually from 1960 to 2010. The second one is the Freedom House Political Rights Index, which is available from 1972 onwards. The variable ranges from 1 to 7, indicating more freedom the closer the value is to 1. We nor-

[13] Results are similar if instead of the political rights index we measure institutions with the civil liberties index.

[13] The ratings are determined by a checklist of 25 questions. The political rights questions are grouped into three subcategories: electoral process, political pluralism and participation, and the functioning of govern-

Table 6: Unconditional and conditional $\beta-$convergence: The role of institutions

	Conditioning on Institutions							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		DemocracyANRR				Political Rights		
	β	β^*	λ	δ	β	β^*	λ	δ
1960s	0.332	0.165	0.651	0.256^a				
	(0.234)	(0.256)	(0.551)	(0.052)				
1970s	0.393^b	0.556^a	-0.773	0.188^a				
	(0.162)	(0.209)	(0.549)	(0.041)				
1980s	-0.200	-0.516^b	2.431^a	0.135^a	-0.227	-0.607^b	3.152^a	0.127^a
	(0.247)	(0.246)	(0.586)	(0.037)	(0.251)	(0.271)	(0.815)	(0.028)
1990s	0.017	-0.146	1.141^a	0.144^a	0.078	-0.126	1.410^b	0.145^a
	(0.178)	(0.200)	(0.419)	(0.030)	(0.175)	(0.216)	(0.637)	(0.026)
2000s	-0.629^a	-0.686^a	0.599	0.095^a	-0.570^a	-0.661^a	0.764	0.120^a
	(0.160)	(0.170)	(0.457)	(0.034)	(0.151)	(0.181)	(0.612)	(0.025)
2010s	-0.436^a	-0.497^a	0.799^c	0.086^b	-0.416^a	-0.559^a	1.161^c	0.123^a
	(0.146)	(0.144)	(0.424)	(0.034)	(0.145)	(0.157)	(0.630)	(0.022)
Constant	0.358	1.456	1.456	-1.686	2.663	4.438^b	4.438^b	-0.638^a
	(2.071)	(2.126)	(2.126)	(0.455)	(2.159)	(2.108)	(2.108)	(0.244)
R^2	0.341	0.392	0.392	0.193	0.348	0.403	0.403	0.223
Obs	724	724	724	724	529	529	529	529
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Dummy outliers	YES	YES	YES	YES	YES	YES	YES	YES

malize the variable to range from 0 to 1, where the greater the value the more democratic a set of institutions is.

Table 6 shows the results of estimating equations (7)-(9) with two measures of institutions for the decades with available data. As the number of observations has changed, we first estimate equation (7) in the reduced samples with available data for institutions. In line with previous findings, (columns (1) and (5)) show a lack of absolute convergence up to the 1990s, and evidence of unconditional convergence from 2000 onward.

The role of institutions is analyzed in the remaining columns. As expected, institutions are an important determinant of the growth rates, revealing that more democratic institutions are associated with higher per capita GDP growth (columns (3) and (7)). However, the effect of institutions on economic growth differs across decades, with a coefficient of λ that is not as statistically significant in some decades as it is, for exam-

ment. The sum of each country's sub-category scores translates to a rating from 1 to 7, with a greater value indicating less freedom.

Table 7: Decomposition of β : The role of institutions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	β	β^*	$(\beta-\beta^*)$	$(\lambda\times\delta)$	β	β^*	$(\beta-\beta^*)$	$(\lambda\times\delta)$
	Controlling for Human Capital							
	HC PWT				*HC BL*			
2000s	-0.575	-1.359	0.784	0.731	-0.575	-1.190	0.615	0.614
2010s	-0.440	-0.904	0.464	0.449	-0.440	-0.965	0.525	0.508
	Controlling for Institutions							
	Democracy				*Political Rights Index*			
2000s	-0.629	-0.686	0.057	0.057	-0.570	-0.661	0.091	0.092
2010s	-0.436	-0.497	0.061	0.069	-0.416	-0.559	0.143	0.142

ple, in the 2000s, when we observe absolute convergence in income levels. Conversely, columns (4) and (8) show that δ is positive and statistically significant at the 1 per cent level in all periods, suggesting that institutions are highly related to the level of GDP.

To compare the contribution of each variable to the process of convergence in GDP in recent decades, Table 7 displays the coefficients of absolute convergence and convergence conditional only to human capital (upper part of the Table), and convergence conditional only to institutions (lower part of the table) for the years 2000s and 2010s. The upper part of the table shows than once we control for human capital, the coefficient of convergence more than doubles. In the decade of the 2000s, the difference between absolute and conditional convergence is 0.784. The convergence coefficient increases from -0.575 when we do not include any control to -1.359 when we control for human capital. In contrast, the lower part of the table shows that the convergence coefficient hardly changes once we control for institutions. For the same period, the difference between unconditional and conditional convergence is 0.057, the coefficient of unconditional convergence is -0.629 and that of convergence conditional on the measure of democracy is -0.686. The difference between absolute and conditional convergence increases to 0.091 when institutions are measured with the political rights index, an increment that is still quite below the increment when we control for human capital.

These results suggest that the role of human capital in the process of convergence in recent decades is not picking up the effect of institutions. We find that human capital has played a stronger role than institutions in the convergence process. While the coefficient of absolute convergence hardly increases when we control for institutions, it more than doubles when we condition on human capital.

4..3 Fixed effects

Acemoglu and Molina (2021) argue that Kremer et al. (2021) results are driven by the estimation of a model that does not account for unobserved permanent determinants of GDP per capita. The correlation between the unobserved fixed effect and the initial level of income will be positive, as richer countries tend to have persistent factors that promote development. The omission of such factors in a model where the dependent variable is the level of income will bias the coefficient of the initial level of income upwards. In equation (7), where the dependent variable is the growth rate, the convergence coefficient β will be biased downward. In fact, Acemoglu and Molina (2021) showed that the omission of country fixed effects biases the convergence coefficient towards zero. They also show that the bias can be time-varying and accounts for the different patterns of convergence over time.

However, controlling for unobserved permanent determinants with the fixed-effect estimator will also lead to biased coefficients in dynamic models in which the lagged dependent variable enters as an explanatory variable (see Nickell, 1981).[14] The coefficient of the initial level of income in a level equation will be biased downward, resulting in an upward bias of β. The bias will be greater the shorter the time period. Moreover, Hauk and Wacziarg (2009) state that the higher speed of convergence with the FE estimator found in the literature is likely to be due to the exacerbation of the measurement error bias. They use simulation methods to assess the bias properties of commonly used estimators in the presence of measurement error and show that the fixed-effects estimator overestimates the speed of convergence, while applying OLS on variables averaged over time provides a more accurate estimate.

As Barro (2015) points out, there is a trade-off between two types of biases: the Nickell bias in the fixed effect estimator, that biases β upwards, and the omitted variable bias in the OLS estimator, that results in a downward bias of β.

[14] By subtracting the mean to eliminate the individual effects, the fixed effect estimator will be biased since the transformed lagged dependent variable and the transformed error term will be correlated. The resulting correlation creates a downward bias in the estimate of the coefficient of the lagged dependent variable.

[14] Hauk and Wacziarg (2009) also find that the GMM estimator of Arellano and Bond (1991), which deals with the fixed effects by taking first differences and using instrumental variables, has a problem of weak instruments in small samples, biasing the GMM estimates toward their fixed-effects counterparts

Table 8: Conditional β-convergence with fixed effects

	Fixed Effects							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			HC PWT			*HC BL*		
	β	β	β^*	λ	δ	β^*	λ	δ
1960s	-1.464[a]	-1.314[a]	-1.297[a]	0.722	0.009	-1.078[a]	-0.775	0.005
	(0.304)	(0.269)	(0.348)	(1.215)	(0.011)	(0.335)	(1.244)	(0.010)
1970s	-1.465[a]	-1.376[a]	-1.470[a]	0.914	0.003	-1.403	0.191	-0.002
	(0.254)	(0.225)	(0.251)	(0.966)	(0.009)	(0.248)	(1.034)	(0.009)
1980s	-1.884[a]	-1.748[a]	-2.347[a]	3.899[a]	0.012	-2.220[a]	3.251[a]	-0.001
	(0.250)	(0.221)	(0.267)	(1.046)	(0.009)	(0.263)	(1.140)	(0.008)
1990s	-1.775[a]	-1.697[a]	-1.595[a]	0.130	0.014[c]	-1.397[a]	-1.503	-0.003
	(0.245)	(0.218)	(0.305)	(1.238)	(0.008)	(0.299)	(1.354)	(0.008)
2000s	-2.522[a]	-2.288[a]	-3.090[a]	4.891[a]	0.007	-2.882[a]	3.780[a]	-0.006
	(0.234)	(0.209)	(0.285)	(1.241)	(0.008)	(0.278)	(1.337)	(0.008)
2010s	-2.285[a]	-2.328[a]	-2.994[a]	4.208[a]	0.001	-2.859[a]	3.591[a]	-0.018[b]
	(0.241)	(0.218)	(0.331)	(1.426)	(0.008)	(0.323)	(1.600)	(0.008)
Constant	1.458[a]	1.540[a]	1.665[a]	1.665[a]	0.391[a]	1.573[a]	1.573[a]	0.403[a]
	(0.330)	(0.291)	(0.291)	(0.291)	(0.011)	(0.290)	(0.290)	(0.011)
R^2	0.266	0.436	0.469	0.469	0.851	0.466	0.466	0.872
Obs	821	821	821	821	821	821	821	821
Countries	140	140	140	140	140	140	140	140
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Dummy outliers	NO	YES	YES	YES	YES	YES	YES	YES

4..3.1 Fixed-effects Estimator

We check the robustness of the results when we control for unobserved permanent determinants of the growth rates. Table 8 shows the results when we estimated equations (7-9) with the fixed effects estimator (FE). The results in columns (1)-(2) show that, conditional to specific characteristics of countries, there is convergence in all periods and β is negative and statistically significant in all decades. As expected, the convergence coefficient with FE is much higher than that with the OLS estimator. This is partly due to the role of time invariant characteristics that are specific to each country, and partly due to the upward bias associated to the FE estimator in dynamic models. The results hold with both measures of human capital.

Columns (3) and (6) show that, when we control for human capital, the convergence coefficient increases, suggesting that even controlling for fixed effects, human capital has played a role in the convergence process. Columns (5) and (8) also indicate that, while human capital is an important determinant of growth rates, there is no evidence that GDP per capita has influenced human capital because the decade coefficients of GDP in equation (9) are not statistically significant. This result minimizes the problem of endogeneity in the growth equation, as more development is not associated with more human capital in the fixed effects model.

In Table 9 we compare the convergence coefficient in different scenarios. It is important to note that, when we include fixed effects, we are controlling for permanent specific characteristics of countries that are difficult to observe or measure. The convergence coefficient in this specification will be convergence conditional to the invariant characteristics of countries and should not be treated as absolute convergence. Thus, we compare the estimated beta coefficients when we do not control for fixed effects (β^{OLS}), when we condition on time-invariant country-specific characteristics with the FE estimator (β^{FE}), when we control for fixed effects and human capital (β^{FE}_{H}), and when we control for fixed effects and institutions (β^{FE}_{IN}).

The results in the upper part of the table show that the convergence coefficient in the decade of the 2000s increases by 1.713 points in the fixed effects model ($\beta^{OLS} - \beta^{FE}$). As stated before, this huge increment is associated with both the role of permanent country-specific characteristics, and the upward bias associated with the fixed effects. The role of human capital conditioning on fixed effects ($\beta^{FE} - \beta^{FE}_{H}$) is shown in column (5). Once we control for human capital the convergence coefficient increases by 0.802 points with the human capital measure from the PWT. Interestingly, this increment is similar to that found in the OLS model (0.784). Although the increment is similar in absolute terms to the one in the OLS model, the interpretation is different. In the OLS model we compare absolute convergence with convergence conditional to human capital. In the fixed-effect model, we asses how convergence, conditional to time-invariant characteristics, increases once we additionally control for human capital. In the decade of the 2010s, the increment in the convergence coefficient once we control for human capital is 0.667.

The lower part of the table shows the results when we control for institutions instead of for human capital. In the fixed effects model, the role of institutions in the process of convergence is in line with previous findings. For the period 2000-2010 the coefficient of convergence hardly changes when we control for the measure of democracy ($\beta^{FE} - \beta^{FE}_{IN} = -0.016$), and increases by 0.179 points when we measure institutions with the Political Rights Index. Similar results are found for the 2010s decade.

[14] We also show the convergence coefficient in each case as the number of observations is different.

Table 9: Decomposition of β -convergence: human capital, fixed effects and institutions

Table 7: Decomposition of $\beta - convergence$

Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Controlling for Human Capital									
	β^{OLS}	β^{FE}	β^{FE}_{H}	$\beta^{OLS} - \beta^{FE}$	$\beta^{FE} - \beta^{FE}_{H}$	β^{OLS}	β^{FE}	β^{FE}_{H}	$\beta^{OLS} - \beta^{FE}$	$\beta^{FE} - \beta^{FE}_{H}$
	HC PWT					HC BL				
2000s	-0.575	-2.288	-3.090	1.713	0.802	-0.575	-2.288	-2.882	1.713	0.594
2010s	-0.440	–2.328	-2.994	1.888	0.667	-0.440	-2.328	-2.859	1.888	0.531
	Controlling for Institutions									
	Democracy					*Political Rights Index*				
	β^{OLS}	β^{FE}	β^{FE}_{IN}	$\beta^{OLS} - \beta^{FE}$	$\beta^{FE} - \beta^{FE}_{IN}$	β^{OLS}	β^{FE}	β^{FE}_{IN}	$\beta^{OLS} - \beta^{FE}$	$\beta^{FE} - \beta^{FE}_{IN}$
2000s	-0.629	-3.013	-2.997	2.384	-0.016	-0.570	-4.698	-4.519	4.128	-0.179
2010s	-0.436	-3.024	-3.019	2.588	-0.005	-0.416	-4.817	-4.710	4.401	-0.107

Overall, these results suggest that the role of human capital in the process of absolute convergence in GDP, observed from the 2000s, is not driven by country-specific characteristics that are omitted in the OLS specification. Even in the presence of fixed effects, the convergence coefficient increases when we control for human capital, and the increment is much higher than when we control for institutions.

4..3.2 Regional dummies

Estimates of the speed of convergence in the influential model of Mankiw et al. (1992) assume initial efficiency to be uncorrelated to the regressors. If that is not the case, the estimates will be biased. A way to deal with initial efficiency is to treat it as a fixed effect, as in Caselli et al. (1996) and Islam (1995). However, as pointed out above, the fixed-effect estimator also comes with its own problems. The Nickel type bias and the exacerbation of measurement error deliver biased and inaccurate estimates.

An alternative approach, suggested by Temple (1998), is to proxy for unobserved initial efficiency by controlling for regional dummies. The idea is that most of the variation in technical efficiency is between regional groups of countries, rather than within them.

In Table 10 we follow this approach and include regional dummies for East Asia and the Pacific, Latin America and the Caribbean, Sub-Saharan African countries, and Advanced economies. Column (1) shows the results of equation (7) adding regional dummies in the set of controls. As expected, the coefficient of the regional dummies is positive for the Advanced economies and East Asia and the Pacific region, and negative for Latin American and Sub-Saharan African countries. If regional dummies are good proxies for initial efficiency, we should interpret the coefficients as conditional convergence, given initial efficiency (β^{RD}).

When we control for regional dummies, we observe convergence from the 1980s onwards, and a large increment in the convergence coefficients. These results are in the same direction as those when we control for fixed effects, though the increment in the convergence coefficients is lower in quantitative terms. The results in the remaining columns show that even controlling for regional dummies, the convergence coefficient increases when we condition on human capital measures.

Table 11 shows the coefficients of absolute convergence, conditional convergence, and the increment in β-convergence for the 2000s and the 2010s when we condition on human capital and when we condition on institutions. Again, the convergence coefficient increases when we condition on human capital, and slightly increases or even reduces

Table 10: Conditional and Unconditional $\beta - convergence$

	Controlling for Human Capital and Regional Dummies						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		h_{PWT}			h_{BL}		
	β	β^*	λ	δ	β^*	λ	δ
1960s	-0.215	-0.715^b	3.108^b	0.124^a	-0.633^c	2.855^b	0.128^a
	(0.206)	(0.357)	(1.236)	(0.020)	(0.332)	(1.244)	(0.019)
1970s	-0.164	-0.320	1.805^c	0.089^a	-0.367	2.126^b	0.090^a
	(0.188)	(0.252)	(0.933)	(0.019)	(0.246)	(0.980)	(0.019)
1980s	-0.636^a	-1.334^a	4.862^a	0.105^a	-1.304^a	5.225^a	0.098^a
	(0.242)	(0.298)	(0.925)	(0.015)	(0.289)	(1.043)	(0.016)
1990s	-0.351^b	-0.123	-0.457	0.126^a	-0.134	-0.593	0.116^a
	(0.147)	(0.255)	(0.989)	(0.013)	(0.250)	(1.125)	(0.014)
2000s	-1.071^a	-1.477^a	3.149^a	0.104^a	-1.465^a	3.373^a	0.098^a
	(0.166)	(0.253)	(0.868)	(0.014)	(0.254)	(0.994)	(0.014)
2010s	-1.019^a	-1.202^a	1.807^b	0.110^a	-1.249^a	2.297^a	0.096^a
	(0.149)	(0.187)	(0.781)	(0.014)	(0.178)	(0.858)	(0.013)
Advanced	0.819^a	0.321	0.321	0.242^a	0.456^b	0.456^b	0.169^a
	(0.251)	(0.238)	(0.238)	(0.027)	(0.229)	(0.229)	(0.025)
East Asia Pacific	1.501^a	1.407^a	1.407^a	0.021	1.354^a	1.354^a	0.038^c
	(0.296)	(0.291)	(0.291)	(0.023)	(0.290)	(0.290)	(0.023)
Latin America	-0.705^a	-0.840^a	-0.840^a	0.045^c	-0.810^a	-0.810^a	0.030
	(0.234)	(0.225)	(0.225)	(0.023)	(0.226)	(0.226)	(0.021)
S.S. Africa	-1.797^a	-1.459^a	-1.459^a	-0.164^a	-1.455^a	-1.455^a	-0.149^a
	(0.261)	(0.252)	(0.252)	(0.025)	(0.253)	(0.253)	(0.023)
Constant	2.336a	2.564^a	2.564^a	0.409^a	2.499^a	2.499^a	0.434^a
	(0.319)	(0.321)	(0.321)	(0.039)	(0.317)	(0.317)	(0.037)
R^2	0.455	0.495	0.495	0.698	0.494	0.494	0.696
Obs	821	821	821	821	821	821	821
Year FE	YES	YES	YES	YES	YES	YES	YES
Dummy outliers	YES	YES	YES	YES	YES	YES	YES

when we condition on institutions.

5. Conclusions

This paper shows evidence of absolute convergence in human capital indicators in a sample of 140 countries. Unconditional to other factors, countries that start with lower levels of human capital have experienced higher growth rates in education in all decades from 1970 to 2020.

The literature has mainly focused on two types of convergence: σ- convergence and β-convergence. We find both types of convergence in human capital. From the late

Table 11: Controlling for Regional Dummies in the decomposition of $\beta-$convergence

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	β	β^*	$(\beta-\beta^*)$	$(\lambda\times\delta)$	β	β^*	$(\beta-\beta^*)$	$(\lambda\times\delta)$
	Controlling for Human Capital							
	HC PWT				*HC BL*			
2000s	-1.071	-1.477	0.406	0.327	-1.071	-1.465	0.394	0.331
2010s	-1.019	-1.202	0.183	0.199	-1.019	-1.249	0.230	0.221
	Controlling for Institutions							
	Democracy				*Political Rights Index*			
2000s	-1.089	-1.038	-0.051	-0.010	-1.069	-1.048	-0.021	0.065
2010s	-0.978	-0.927	-0.051	-0.023	-0.989	-1.036	0.047	0.102

1970s, there is a decline in the dispersion of human capital across countries, measured as the variance of the log of human capital. We also find an inverse relationship between the initial levels of human capital and its subsequent growth rates. This process of β-convergence in human capital has been increasing over time.

Convergence in human capital has been the result of a speeding-up of the regions at the bottom, a slowdown of the regions at the top, and a relative stability of the regions in the middle. Countries in South-Asia, for example, were ranked among those with the lowest levels of human capital in 1960. In 1980, this region started speeding up in human capital investment rates and, from 1990 onward, South Asia is the region with the highest growth rates in human capital. At the other extreme, the advanced economies started with the highest level of education in 1960, but experienced the lowest growth rates in human capital between 2010 and 2020. In the middle, countries in Latin America and the Caribbean have ranked fourth in terms of human capital growth rates in almost all decades.

Recent empirical evidence has shown a change in the slope in the relationship between per capita income and its growth rates from the 2000s, suggesting absolute convergence in per capita income. As convergence in human capital preceded that of per capita income, human capital may have contributed to the process of absolute convergence in per capita income observed in recent years. We use the omitted variable bias formula to test whether human capital has played any role in explaining convergence in per capita income from 2000 to 2019. We find that the coefficient of $\beta-$ convergence, conditional to the initial level of human capital, is more than double that the coefficient of unconditional convergence. The difference between both coefficients is explained by the role of human capital.

We show that this result is robust to alternative measures of per capita GDP and even holds after we control for country fixed effects. Additionally, this result is not driven by the role of institutions in the convergence process either. In fact, we find a much higher convergence coefficient when we condition on human capital than when we do it on institutions.

Finding absolute convergence in per capita income is a new phenomenon among countries with distinct levels of development. We show that in a sample that represents most of the countries in the world, the patterns of human capital convergence have helped to account for the observed patterns of income convergence in the recent decades. This evidence leads to the suggestion that human capital is not only an important determinant of growth rates, but can also increase the speed of convergence and close the gap in GDP per capita between poor and rich economies.

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