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Human Capital, Age Structure and Economic Growth: Evidence from a New Dataset

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Abstract

This paper discusses a new dataset on educational attainment levels by age and sex for 120 countries in the period 1970-2000 which has been reconstructed using demographic multistate back-projection methods. Using this unique dataset, we show that the differences in the education level of the younger age groups explain the differences in income per capita across countries significantly better than aggregate measures such as the education level of the entire adult population. We also present evidence that in developed countries, the education of the younger adults contributes significantly to the adoption of technology.

Acknowledgments

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Introduction

Finding a robust empirical relationship between measures of educational attainment and long-run economic growth turns out to be a hard task. Cross-country growth regressions tend to show that changes in educational attainment are unrelated to economic growth (see, for example, Benhabib and Spiegel 1994; Pritchett 2001). The difficulty of matching microeconometric evidence (where empirical studies show high and significant returns to education) with results at the macroeconomic level has been the source of a growing body of literature which tries to solve this puzzle. While Temple (1999) claims that the lack of relationship may be due to outliers, most of this literature attributes the existence of the puzzle to deficiencies in the human capital data (see Krueger and Lindahl 2001; Cohen and Soto 2001; De la Fuente and Domenech, 2006).

In this paper we discuss and analyze a new dataset of educational attainment by five-year age groups for 120 countries for the period 1970-2000 (Lutz et al. 2007). The dataset is reconstructed using demographic methods to back-project the population by four levels of educational attainment and sex along cohort lines. Unlike earlier reconstruction efforts, these data also incorporate the fact that people with different levels of education tend to have different mortality rates. In addition, by starting from one empirical distribution around the year 2000 and then going backward in time, the definition of education categories is strictly consistent over time. The fact that not only the mean years of schooling but also the full distribution over educational attainment categories are available by age and sex opens new avenues of research by assessing the demographic structure of human capital directly.

Using this unique dataset, we conduct two empirical studies aimed at assessing the importance of the demographic dimension of human capital for explaining differences in income and income growth across countries. First, based on the calibration exercise carried out in Hall and Jones (1999), we present evidence that the differences in the education level of the younger age groups are better able to explain the differences in income per capita across countries than aggregate measures which summarize the educational attainment of the adult population. We also present empirical evidence on the importance of considering the age structure of human capital when considering education-driven technology absorption. Using the methodological setting put forward by Benhabib and Spiegel (1994), we find evidence that in developed economies the education levels of the younger age groups play an active role in technology adoption, while human capital at older ages does not cause significant

technological absorption for OECD countries. In developing economies, education levels at all age groups are found to cause significant interactions with the technological gap and thus are relevant for technology adoption.

Following the introduction, we present the method used for reconstructing the dataset of human capital by sex and age group. The third section reports evidence on the improvement caused by considering the demographic dimension of human capital when evaluating the determinants of differences in income per capita across countries. The fourth section re-estimates the model put forward by Benhabib and Spiegel (1994) using human capital data for different age groups and subsamples, in order to assess the importance of the demographic dimension of human capital in the process of technology absorption. The paper closes with the conclusions.

Reconstructing Educational Attainment Distributions by Age and Sex: Multistate Back Projections

At any point in time the distribution of the population by age, sex and level of educational attainment reflects the history of changes in the proportions of a cohort that attended school and reached certain educational levels. Since formal education typically happens in childhood and youth, the current educational attainment distribution of 50-54 year old women, for instance, reflects education conditions and school enrolment of more than 30 years ago. This is clearly visible as an example in Figure 1 for the educational age pyramid of Singapore in the year 2000. While young women in Singapore today have one of the highest educational levels in the world, with more than half having completed some form of tertiary education, in their mothers' generation (those women aged above 50 in 2000), more than half had never received any formal education. This is because some 40 years ago, Singapore was still a poor developing country with low school enrolment rates. Only thereafter did Singapore make a most impressive progress in education of both women and men. This history is well reflected in today's age pattern of education. All of these important age-specific, non-linear trends of improving educational attainment in Singapore that potentially may matter greatly for the specific course of economic growth, do not appear when looking only at the smooth trend in mean years of schooling of the entire adult population above age 25, as plotted in Figure 2.

The back-projection exercise recently carried out as a joint effort by the International Institute for Applied Systems Analysis (IIASA) and the Vienna Institute of Demography (VID) of the Austrian Academy of Sciences utilizes the fact that much of a population's education history is still reflected in its current structure (Lutz et al. 2007). It goes back along cohort lines in five-year steps by deriving, e.g., the proportion without any formal schooling among 50-54 year old women in 1995 from that of 55-59 year olds in 2000. There are only three possible factors that can cause these two proportions to differ: differential mortality, differential migration and women who still acquire formal education after the age of 55. While such late educational transitions are typically irrelevant, differential mortality is a major issue because there is strong evidence in virtually all countries where such data exist that higher educational groups have significantly lower levels of mortality, presumably through better access to information, healthier lifestyles and better economic standing. Although this issue is

mentioned in the literature of education data (see Cohen and Soto 2001), it is not explicitly dealt with when reconstructing human capital data.
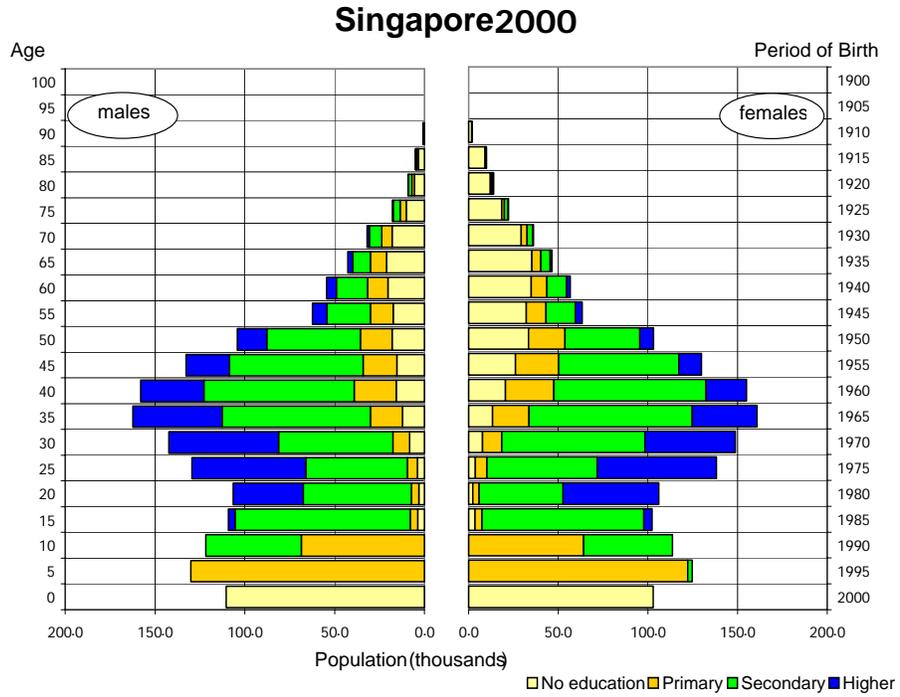

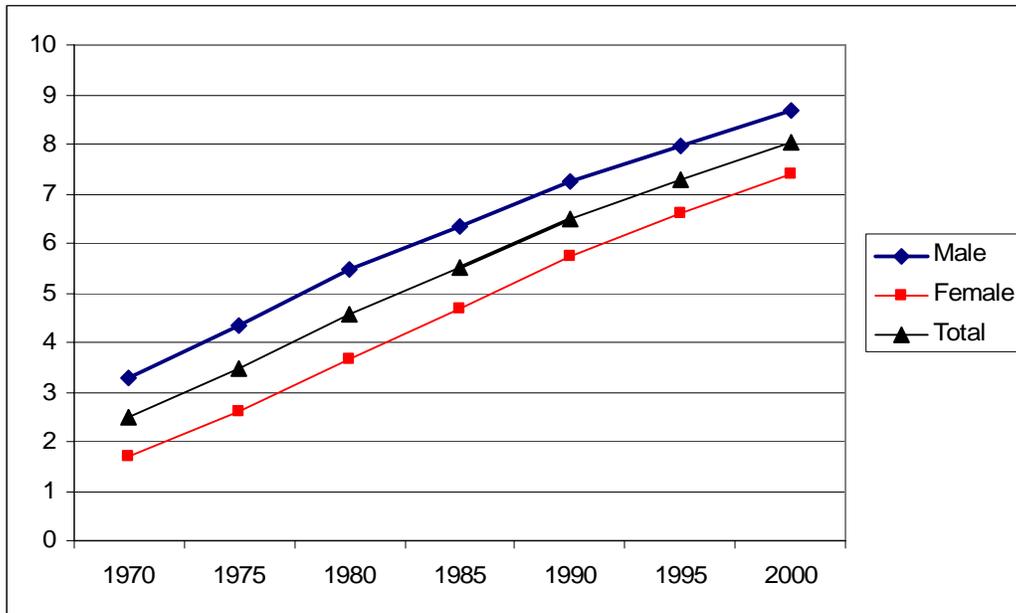Figure 1. Age and education pyramid for Singapore, 2000.

Figure 2. Mean years of schooling of the 25+ population for Singapore. Source: Lutz et al. (forthcoming).

Lutz et al. (2007) provide a detailed account of all the specific assumptions that had to be made as part of this reconstruction exercise, discuss their plausibility and provide sensitivity analyses. The method can be summarized as follows: First, for every country an empirical distribution of the population by age, sex and four categories of educational attainment (no formal education, some primary, completed lower secondary, completed first level of tertiary) was retrieved for the year 2000. These data mostly stem from national censuses or Demographic and Health Surveys (DHS). At this stage it was important to assure the consistency of educational categories across all countries and some reclassification had to be made. Second, we draw on an existing United Nations (2005) dataset which provides estimates of the age and sex structure in five-year intervals since 1950 for every country in the world. For this reason our effort did not have to reconstruct the absolute sizes of the populations by individual age groups, but only the proportions with different education levels in each age group of men and women. This also made the necessary demographic assumptions a lot easier, since it was not necessary to estimate the overall level of mortality or the total volume of migration (which is given in the UN data), but only to consider to what degree these demographic forces differ by level of education. While for migration the default assumption was that there are no educational differentials, for mortality we assumed a consistent pattern that life expectancy at age 15 differs by five years between the lowest and the highest educational category (with the difference between no education and some primary being one year and the other differences being two years each). This assumption was based on an assessment of a selection of countries from different parts of the world for which such data exist.

A further problem arises from the fact that in the empirical data, the oldest age group is typically an open-ended category such as 65+ or 70+. When going back along cohort lines, those aged 70+ in 2000 are 40+ in 1970. To get information for the closed intervals 40-44 to 60-64, we need to make assumptions about the distributions across age and education categories in these open intervals which were based (unless empirical information was available) on exponential trend extrapolation of the proportions in the adjacent closed age groups. This source of uncertainty is the reason why it was decided to stop the reconstruction in 1970 and not go back further into history, as the assumptions would have become progressively more restrictive. Another set of assumptions referred to the ages at which transitions from one educational category to another were made. Since the reconstruction is only performed for the population above age 15, this only concerned transitions to tertiary and to a lesser extent to secondary level. Lutz et al. (2007) provide further technical details on the reconstruction of the dataset.

Table 1. Reconstruction output for India.

Population Distribution ('000) by Age, Sex and Level of Education plus Means Years of Schooling

		Males					Females				
		No Edu.	Primary	Secondary	Tertiary	MYS	No Edu.	Primary	Secondary	Tertiary	MYS
2000	15-19	8867.9	14274.4	29681.6	0.0	6.6	14388.4	12058.4	22819.5	0.0	5.5
	20-24	8917.9	10326.9	23088.3	3906.1	7.2	17138.4	8804.1	14025.1	2813.2	5.1
	25-29	10535.7	10117.4	18153.7	5191.1	6.9	19288.5	8470.7	9809.7	2893.5	4.4
	30-34	11251.9	9467.0	14566.2	4328.1	6.4	19787.5	7470.4	7115.4	2013.2	3.6
	35-39	11258.2	9195.7	11243.9	3274.6	5.7	18600.2	6753.1	5345.5	1387.1	3.2
	40-44	10281.5	8067.7	9242.1	2785.4	5.6	16974.7	5578.5	4153.2	1103.6	2.9
	45-49	8523.5	6780.7	7453.6	2298.9	5.5	14878.0	4503.7	2970.6	751.0	2.6
	50-54	7591.1	5223.6	5313.0	1683.8	5.1	13297.3	3362.2	1982.0	507.8	2.1
	55-59	6255.8	4633.0	3937.7	1157.7	4.7	12067.1	2639.4	1209.5	262.1	1.6
	60-64	6389.9	3614.5	2346.7	619.9	3.6	10929.7	1818.6	680.3	132.3	1.2
	65+	12124.9	7331.6	3515.5	855.0	3.2	21509.3	3534.2	1022.4	161.2	1.0
	15+	*101998.4*	*89032.5*	*128542.2*	*26100.7*	*5.9*	*178859.1*	*64993.3*	*71133.4*	*12025.2*	*3.5*
	25+	*84212.5*	*64431.2*	*75772.3*	*22194.6*	*5.5*	*147332.3*	*44130.9*	*34288.8*	*9211.9*	*2.8*
1995	15-19	9037.9	12640.2	25056.7	0.0	6.4	17354.4	10005.4	15873.4	0.0	4.5
	20-24	10732.7	10289.7	21911.3	1750.8	6.4	19567.9	8578.8	11851.1	971.9	4.1
	25-29	11500.2	9656.6	16268.0	2924.7	6.1	20084.4	7568.3	7862.4	1352.1	3.5
	30-34	11536.8	9399.7	11442.3	3320.6	5.7	18887.4	6843.0	5397.3	1396.4	3.2
	35-39	10588.1	8281.5	9432.0	2829.1	5.5	17280.5	5665.8	4201.1	1112.5	2.9
	40-44	8861.4	7020.2	7658.0	2346.7	5.5	15225.0	4596.4	3017.2	759.5	2.5
	45-49	8030.3	5496.0	5533.5	1738.2	5.0	13759.4	3466.9	2030.7	517.2	2.1
	50-54	6793.5	4997.1	4192.0	1218.0	4.7	12707.1	2765.5	1255.5	269.7	1.6
	55-59	7240.8	4061.0	2592.5	674.2	3.6	11914.7	1968.1	726.2	139.4	1.1
	60-64	5827.9	3635.1	1925.9	491.7	3.5	9856.3	1678.3	503.9	82.4	1.0
	65+	10960.9	6362.3	2627.2	573.2	2.9	18241.4	2854.5	755.0	108.5	0.9
	15+	*101110.5*	*81839.4*	*108639.5*	*17867.2*	*5.5*	*174878.5*	*55991.0*	*53473.7*	*6709.6*	*2.9*
	25+	*81339.9*	*58909.5*	*61671.5*	*16116.4*	*5.1*	*137956.1*	*37406.7*	*25749.2*	*5737.7*	*2.4*
1990	15-19	10881.6	12495.4	21814.1	0.0	5.9	19852.1	9622.2	12012.6	0.0	3.8
	20-24	11699.3	9807.2	18442.1	984.7	5.8	20409.8	7676.1	8857.0	454.4	3.3
	25-29	11763.3	9564.4	12719.6	2237.6	5.5	19202.8	6942.6	5925.3	938.3	3.1
	30-34	10830.8	8449.6	9579.6	2862.4	5.5	17578.6	5750.2	4246.3	1120.6	2.9
	35-39	9121.9	7202.8	7810.5	2381.2	5.4	15531.1	4677.1	3056.3	766.4	2.5
	40-44	8356.3	5695.0	5689.3	1774.8	5.0	14116.7	3546.9	2066.8	523.9	2.1
	45-49	7208.0	5273.1	4378.2	1260.2	4.7	13196.2	2861.5	1290.3	275.4	1.6
	50-54	7888.8	4394.3	2768.8	711.2	3.5	12607.9	2071.9	757.1	144.0	1.1
	55-59	6654.3	4115.1	2143.9	538.5	3.4	10833.3	1831.2	542.0	87.5	1.0
	60-64	5898.3	3093.4	1317.9	295.8	2.8	8846.3	1281.9	340.2	51.0	0.9
	65+	9591.1	5771.8	2147.5	430.8	2.8	15616.8	2473.2	607.7	79.6	0.9
	15+	*99893.6*	*75862.0*	*88811.4*	*13477.3*	*5.0*	*167791.6*	*48734.8*	*39701.5*	*4441.0*	*2.5*
	25+	*77312.7*	*53559.4*	*48555.2*	*12492.5*	*4.7*	*127529.7*	*31436.5*	*18831.9*	*3986.6*	*2.0*
1985	15-19	11855.6	11670.5	17853.1	0.0	5.4	20725.8	8477.7	8705.4	0.0	3.1
	20-24	11949.5	9698.4	14360.3	751.9	5.2	19535.4	7047.5	6622.6	315.3	2.9
	25-29	11028.6	8585.1	10657.8	1925.2	5.3	17903.3	5842.7	4673.4	753.4	2.8
	30-34	9328.2	7345.7	7926.4	2406.8	5.4	15830.7	4755.1	3093.1	772.6	2.5
	35-39	8607.0	5845.7	5802.9	1800.6	5.0	14433.0	3616.6	2096.9	529.3	2.1
	40-44	7516.2	5474.5	4508.2	1288.4	4.6	13574.8	2934.9	1315.9	279.5	1.6
	45-49	8389.9	4647.4	2897.0	737.0	3.5	13142.4	2151.7	780.5	147.5	1.1
	50-54	7290.4	4477.5	2301.3	570.9	3.4	11528.3	1938.4	567.9	90.8	1.0
	55-59	6782.5	3526.7	1477.0	326.1	2.8	9805.3	1410.4	368.8	54.5	0.8
	60-64	4816.4	3029.9	1286.6	267.6	3.0	7492.3	1264.7	344.5	48.2	1.0
	65+	9001.9	5065.4	1550.1	280.0	2.5	13718.1	1996.6	416.7	47.4	0.8
	15+	*96566.2*	*69366.8*	*70620.6*	*10354.6*	*4.6*	*157689.5*	*41436.2*	*28985.8*	*3038.3*	*2.1*
	25+	*72761.2*	*47997.9*	*38407.3*	*9602.7*	*4.3*	*117428.1*	*25911.0*	*13657.8*	*2723.0*	*1.7*
1980	15-19	12124.0	11185.0	13897.8	0.0	4.9	19887.7	7681.7	6496.5	0.0	2.8
	20-24	11218.9	8715.7	12077.1	647.3	5.0	18265.2	5946.3	5243.3	253.6	2.7
	25-29	9515.7	7475.0	8842.2	1620.1	5.2	16170.3	4844.6	3397.0	520.3	2.4
	30-34	8821.0	5972.8	5898.0	1821.9	4.9	14751.4	3686.1	2126.5	534.4	2.1
	35-39	7765.3	5634.4	4608.9	1309.5	4.6	13916.4	3000.1	1338.0	282.8	1.6
	40-44	8776.1	4838.1	2990.1	754.8	3.5	13560.5	2213.2	798.2	150.0	1.1
	45-49	7798.0	4760.6	2420.0	594.2	3.3	12069.4	2021.5	587.9	93.3	1.0
	50-54	7478.9	3860.4	1594.8	347.5	2.7	10492.9	1501.2	388.5	56.9	0.8
	55-59	5600.2	3491.5	1457.4	298.1	3.0	8381.2	1404.1	376.9	51.9	1.0
	60-64	4653.8	2744.6	953.4	178.4	2.7	6842.8	1061.3	245.0	29.7	0.8
	65+	8412.5	4415.1	1117.4	181.7	2.2	11872.4	1587.0	281.4	27.8	0.7
	15+	*92164.5*	*63093.3*	*55857.0*	*7753.6*	*4.2*	*146210.2*	*34947.2*	*21279.2*	*2000.7*	*1.8*
	25+	*68821.6*	*43192.6*	*29882.1*	*7106.2*	*3.9*	*108057.3*	*21319.2*	*9539.4*	*1747.1*	*1.5*
1975	15-19	11432.0	10018.4	11758.8	0.0	4.7	18640.1	6470.1	5160.1	0.0	2.5
	20-24	9734.9	7633.5	10097.2	548.3	4.9	16561.5	4949.8	3807.7	175.8	2.3
	25-29	9041.1	6108.5	6625.1	1233.4	4.8	15135.9	3772.4	2347.1	361.6	2.0
	30-34	7987.6	5780.0	4704.7	1331.3	4.6	14305.1	3075.3	1364.7	287.2	1.6
	35-39	9077.4	4987.0	3062.6	769.0	3.5	13978.3	2274.9	816.0	152.6	1.1
	40-44	8147.1	4951.9	2496.6	608.7	3.3	12495.1	2086.1	603.2	95.2	1.0
	45-49	7929.5	4070.2	1663.5	359.1	2.7	10964.8	1562.6	401.4	58.3	0.8
	50-54	6084.7	3767.5	1551.4	313.4	3.0	8912.8	1485.2	394.5	53.8	1.0
	55-59	5247.7	3068.4	1047.8	192.9	2.6	7517.2	1157.2	263.2	31.5	0.8
	60-64	4367.0	2395.8	677.5	113.5	2.3	6129.7	869.5	169.1	17.8	0.7
	65+	7549.0	3685.9	772.8	113.3	1.9	10180.0	1245.6	186.6	15.8	0.6
	15+	*86597.9*	*56467.0*	*44458.1*	*5583.0*	*3.9*	*134820.6*	*28948.8*	*15513.8*	*1249.6*	*1.6*
	25+	*65431.1*	*38815.2*	*22602.0*	*5034.7*	*3.4*	*99619.0*	*17528.0*	*6545.9*	*1073.8*	*1.2*
1970	15-19	9945.9	8748.9	9856.3	0.0	4.6	16966.1	5358.5	3747.0	0.0	2.2
	20-24	9276.6	6254.6	7593.7	418.0	4.5	15567.7	3868.1	2638.6	122.4	1.9
	25-29	8211.2	5926.7	5253.1	902.4	4.4	14740.1	3158.6	1491.2	194.6	1.5
	30-34	9359.4	5125.9	3129.8	782.1	3.4	14430.0	2340.4	834.6	155.2	1.1
	35-39	8455.1	5119.2	2562.3	620.7	3.3	12937.9	2153.0	618.7	97.1	1.0
	40-44	8309.8	4244.9	1719.0	368.0	2.7	11400.4	1619.0	413.2	59.7	0.8
	45-49	6481.7	3989.3	1623.8	324.5	2.9	9361.2	1553.3	409.3	55.4	1.0
	50-54	5726.2	3324.2	1119.1	203.2	2.6	8043.9	1231.2	277.0	32.8	0.8
	55-59	4952.7	2693.6	748.4	123.3	2.3	6796.8	956.6	183.3	19.0	0.7
	60-64	4078.6	2071.7	477.6	71.7	2.0	5423.5	699.3	113.8	10.2	0.6
	65+	6672.9	3055.0	543.5	72.7	1.7	8797.7	996.6	128.9	9.6	0.5
	15+	*81470.0*	*50553.8*	*34626.7*	*3886.6*	*3.5*	*124465.3*	*23934.6*	*10855.7*	*755.9*	*1.3*
	25+	*62247.5*	*35550.3*	*17176.7*	*3468.6*	*3.1*	*91931.6*	*14708.1*	*4470.1*	*633.6*	*1.0*

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Table 1 provides the standard output table for India as an example. These tables are given for absolute numbers of men and women as well as the total populations by five-year age groups and the four levels of educational attainment for 120 countries (see Lutz et al. 2007). There are also tables giving the corresponding proportions among all people in the corresponding age group. The bottom line of each table gives the distribution across educational categories for all adult age groups together; the right-hand margin gives the summary measure of the average level of education for individual age groups in the form of mean years of schooling. Although the estimation of this indicator requires additional assumptions in terms of the average years of schooling it takes to become a member of a certain educational attainment category, it was decided to provide it in order to facilitate comparison to other datasets that only provide mean years of schooling. Finally, the number in the lower right corner of the matrix gives the mean year of schooling for the entire adult population above age 25. This is the number most frequently used in economic studies. As Table 1 shows, this single number has only limited information content and even in terms of mean years of schooling hides the significant improvement in the educational level of younger Indian women during the 1980s. Having the full matrix available for analysis significantly expands the possibility for analysis not only along the age dimension, as will be done here, but also with respect to different mixes of primary, secondary and tertiary education in the population.

Figure 3 compares the aggregated IIASA-VID and Barro-Lee (Barro and Lee 2001) data for mean years of schooling of the adult population over 25 years of age for the years 1970 and 2000. The relative ordering of the countries in the sample in terms of education level does not change strongly when comparing the Barro-Lee dataset and the IIASA-VID dataset, although the estimates of mean years of schooling in the IIASA-VID data tend to be systematically higher than in the Barro-Lee data. The distribution of changes in mean years of schooling, however, differs significantly across datasets, as can be observed in Figure 3. While the IIASA-VID dataset presents a higher dispersion in changes in mean years of schooling when comparing the years 2000 and 1970, the standard deviation of the *growth rate* of mean years of schooling appears higher in the Barro-Lee dataset, a feature which is caused mainly by the observation in Nepal, which started with minimal levels of education in accordance with the Barro-Lee dataset (0.04 mean years of schooling, as compared to 0.48 according to the IIASA-VID dataset).[1] The countries that present higher changes in mean years of schooling in the Barro-Lee dataset as compared to the IIASA-VID dataset tend to be highly developed economies (some examples are Japan, the Netherlands, New Zealand, Norway, Sweden, Switzerland, United Kingdom or the United States), while the IIASA-VID dataset presents higher changes in the aggregate educational variable for practically all East Asian countries which are considered "growth miracles" in the last decades, as well as most African countries in the sample.

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[1] De la Fuente and Domenech (2006) comment on other implausible developments in the change of mean years of schooling for the Barro-Lee dataset.
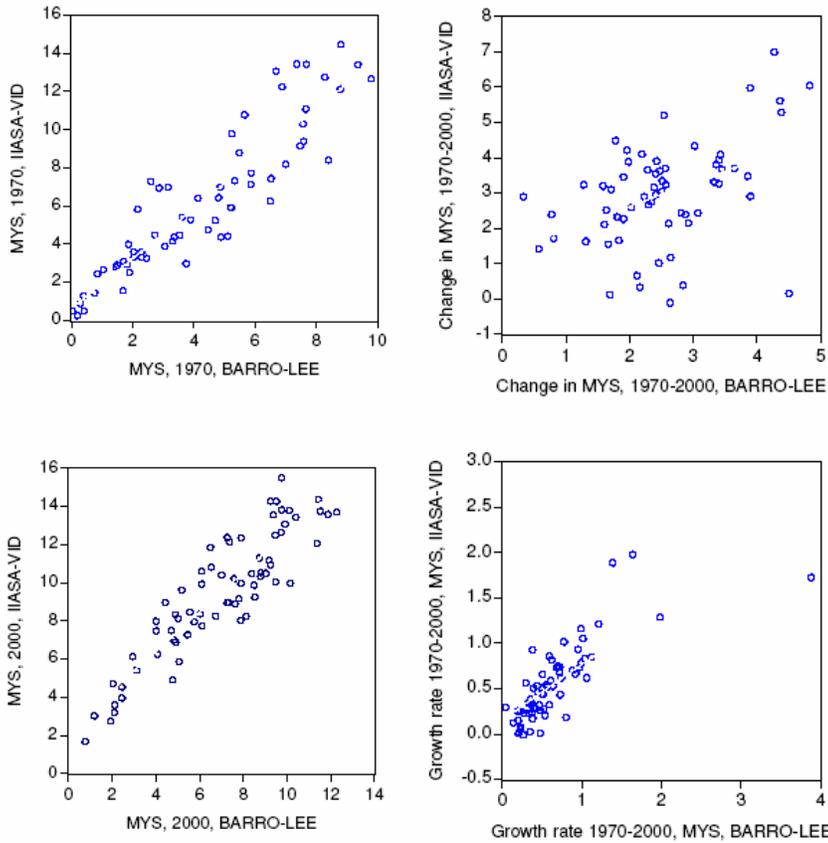
Figure 3. Mean years of schooling and changes in mean years of schooling of the total population above age 25, Barro-Lee and IIASA-VID datasets.

Revisiting the Contribution of Human Capital to Income Differences: The Role of the Age Dimension

In this section we assess the importance of the age dimension of human capital in explaining cross-country differences in income per capita. Following a production function as in Hall and Jones (1999), we decompose differences in income per capita across countries into differences in physical, human capital and total factor productivity.

Assume that output Y_i in country i is produced according to

$$Y_i = K_i^\alpha (A_i H_i)^{1-\alpha} \tag{1}$$

where K_i denotes the stock of physical capital, H_i is the amount of human-capital augmented labor used in production and A_i is labor-augmenting technology, the Solow residual (which is obtained empirically as the part of GDP per capita that cannot be explained by the inputs of production). The human capital stock, H_i, is given by

$$H_i = L_i \exp(\phi(E_i))$$

where E_i are mean years of schooling in country i. As in Hall and Jones (1999), $\phi(.)$ will be assumed piecewise-linear, so that the return to education for the first four years of education equals 0.134; for the following four years it is 0.101; and for the years over eight it is 0.068. These returns to schooling are based on microeconomic evidence reported in Hall and Jones (1999) and are assumed equal across countries.

Rewriting Eq. (1) in per capita terms,

$$y_i = \left(\frac{K_i}{Y_i}\right)^{\alpha/(1-\alpha)} \frac{H_i}{L_i} A_i, \tag{2}$$

that is, differences in GDP per capita (y_i) can be decomposed into differences in the capital-output ratio, differences in educational attainment per worker and differences in productivity.

In order to make our results comparable to those in Hall and Jones (1999), we use the same data,[2] with the exception of the education variable. The decomposition given by Eq. (2) is carried out using data for income per capita; the number of workers in 1988 from the Penn World Tables (Summers and Heston 1991); and physical capital data obtained from investment rates using the perpetual inventory method for 91 countries. Table 2 presents the results of this decomposition using alternatively the Barro-Lee dataset (as in Hall and Jones 1999) and the IIASA-VID dataset for constructing the human capital variable. We normalized the US data to one and computed the decomposition as compared to the US values. We report the mean and standard deviation of each one of the components. The standard deviation of the Solow residual represents, thus, the part of income differences which is left unexplained by the decomposition. In all the calculations, we set $\alpha=1/3$. For the case of the IIASA-VID dataset, we calculated the human capital variable based on the whole adult population over 25 and on different 15-year age groups corresponding to the average years of schooling of the population aged 25-39, 40-54 and 55-65+.[3]

Table 2. Income per capita decomposition: Disaggregated data by age.

| | Y/L | K/Y | Contribution from | | | | | | | | | |
| | | | H/L | | | | | A | | | | |
			BL	25+	25-39	40-54	55-65+	BL	25+	25-39	40-54	55-65+
Average	0.325	0.873	0.591	0.685	0.739	0.648	0.596	0.532	0.464	0.427	0.489	0.545
Stand. dev.	0.285	0.231	0.172	0.197	0.197	0.211	0.222	0.323	0.290	0.265	0.298	0.354
F-test									1.048	4.283**	0.838	0.251

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[2] The dataset for Hall and Jones (1999) is available at http://www.stanford.edu/~chadj.

[3] We evaluated the human capital contribution for the IIASA/VID dataset with observations of 1990. We also considered groups overlapping this division (30-44, 34-49, etc.). Since the results imply systematically a monotonic relationship between age-specific human capital and explanatory power, we only present these three groups to illustrate the differences. Detailed results are available from the authors upon request.

Table 2 also presents the results of an F-test for equality of variances of the Solow residual between the resulting residual from the Barro-Lee dataset and that of each one of the cases for the IIASA-VID dataset. In all cases, with the exception of the case where the human capital variable is computed from the oldest population subgroup, the human capital contributions implied by the IIASA/VID dataset are better able to explain differences in income across countries, as implied by the lower level and standard deviation of the Solow residual for the full sample of countries. The levels of human capital implied by the IIASA/VID dataset tend to be higher than those implied by the Barro-Lee dataset. A significant improvement of the explanatory power of the growth accounting exercise can be found when using human capital data from younger cohorts. Using the human capital variable for the cohort with ages 25-40 results in the smallest average size and dispersion of the Solow residual. We tested for equality of variances using the Brown-Forsythe test (Brown and Forsythe 1974), since the empirical distributions of the Solow residual tend to be highly skewed. The test rejects equality of variances for the decomposition obtained with the youngest cohort, which implies that differences in education of the youngest groups of the labor force are better able to explain differences in income per capita across countries.

Human Capital, Age Structure and Technology Adoption

The effect of education on growth can be viewed, using the Nelson-Phelps paradigm, as being channeled through technology adoption (see Nelson and Phelps 1966; Benhabib and Spiegel 1994, 2005). The distance between the technological frontier and the level of technology of a given country is thus the variable that interacts with the level of education in order to render an effect on long run economic growth.

Following Benhabib and Spiegel (1994) we will assess empirically the influence of human capital on growth and technology adoption using cross-country growth regressions. The preferred empirical specification in Benahbib and Spiegel (1994) is as follows:

$$(\ln Y_{iT} - \ln Y_{i0}) = \beta_0 + \beta_1 H_i + \beta_2 H_i\left(\frac{y_{max}}{y_i}\right) + \beta_3(\ln K_{iT} - \ln K_{i0}) + \beta_4(\ln L_{iT} - \ln L_{i0}) + \varepsilon_i$$

where Y_i is GDP in country i, K_i is the physical capital stock in country i, L_i is labor force in country i, H_i is the human capital variable (average of mean years of schooling in the labor force between period 0 and period T, from Kyriacou (1991) in the case of Benhabib and Spiegel 1994), (y_{max}/y_i) is a measure of the catching-up effect (the ratio of income per capita in the richest country of the sample and country i), which can be interpreted as the technological gap of country i with respect to the technological leader. Human capital in the model is assumed to affect technological progress by having an influence on domestic innovation (the term $\beta_1 H_i$) and on the diffusion foreign technology (the term $\beta_2 H_i(y_{max}/y_i)$).

Using data for the period 1965-1985, as in Benhabib and Spiegel (1994), for the available sample of countries, Table 3 presents the results of the estimation using the human capital variable in Kyriacou (1991) and using the IIASA/VID dataset. The

results are presented for the full sample and for the subsamples of OECD and non-OECD countries.[4] Using the Kyriacou (1991) dataset, the effect of education levels on technology adoption only appears significant for the non-OECD sample. For the IIASA/VID dataset the results for the OECD sample implies a 10 percent significant parameter for this interaction, and the human capital variable without interaction appears significant and negative when using the full sample and the non-OECD subgroup. Notice that the results for the non-OECD group imply that the overall effect of human capital on growth is positive for countries with a level of GDP per worker lower than 10 percent of the richest country in the sample.

Table 3. Benhabib and Spiegel (1994) regressions.

	Kyriacou data			IIASA/VID data		
	Full sample	OECD	Non-OECD	Full sample	OECD	Non-OECD
H	-0.014 (0.014)	-0.015 (0.012)	-0.025 (0.022)	-0.023** (0.009)	-0.018 (0.011)	-0.053** (0.022)
$H\left(\frac{y_{max}}{y}\right)$	0.006*** (0.001)	0.004 (0.003)	0.007*** (0.001)	0.005*** (0.001)	0.007* (0.004)	0.005*** (0.002)
$\ln K_{iT} - \ln K_{i0}$	0.472*** (0.072)	0.511*** (0.106)	0.482*** (0.092)	0.502*** (0.063)	0.433*** (0.137)	0.532*** (0.1016)
$\ln L_{iT} - \ln L_{i0}$	0.188 (0.164)	0.197 (0.160)	0.264 (0.278)	0.064 (0.166)	0.262 (0.135)	0.090 (0.345)
Obs.	78	19	59	62	19	43
$\bar{R}^2$	0.70	0.90	0.67	0.63	0.90	0.58

Using the age dimension of the IIASA/VID dataset, the estimation gives new insights to the differences in the process of technology absorption between developed and developing countries. We re-ran the regressions using education by age groups for the OECD and non-OECD subsamples. Each human capital variable was included individually in each regression in order to avoid multicollinearity. The estimated parameters for each regression (together with twice the standard deviation of the estimates) are presented in Figures 4, 5 and 6.

While the estimates for the full sample and the non-OECD countries do not appear significantly different across age groups, interesting differences appear if we consider the two subsamples. For the OECD sample the human capital levels corresponding to the younger age groups interact significantly with the level of development in the process of technology adoption through human capital. In particular, the level of education of the age groups up to 35 years present a significant and positive attached parameter. However, the education level of older age groups does not appear significantly related to growth through technology absorption for the group of developed economies. This could have to do with relatively low pension ages in the OECD as well as with a mechanism by which innovation associated with younger age is more important at higher levels of income than in developing countries, where growth is more driven by imitations.

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[4] While the human capital variable in the Benhabib and Spiegel (1994) results refer to the period 1965-1985, in the case of the IIASA/VID dataset they are constructed for the period 1970-1985, due to data availability.
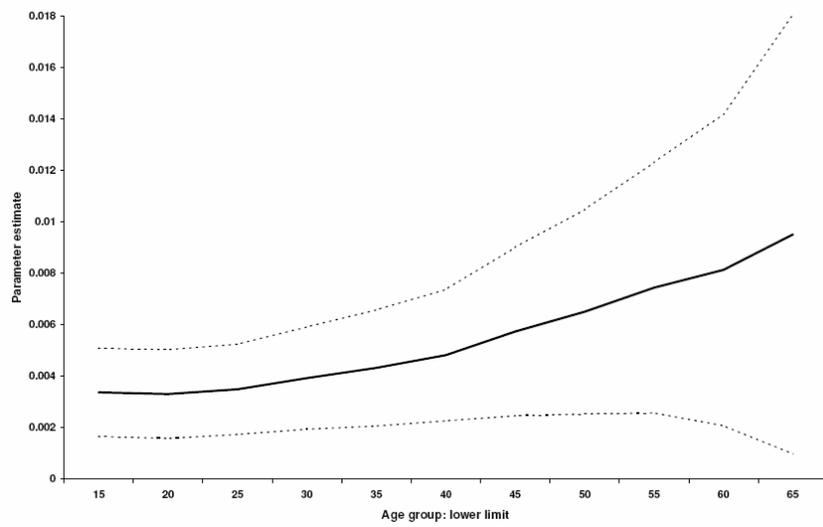
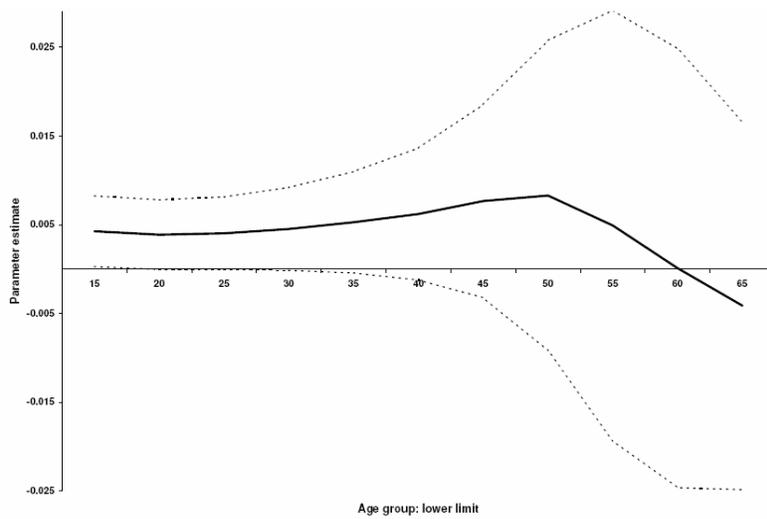Figure 4. Estimates of the absorption parameter: Full sample.

Figure 5. Estimates of the absorption parameter: OECD sample.
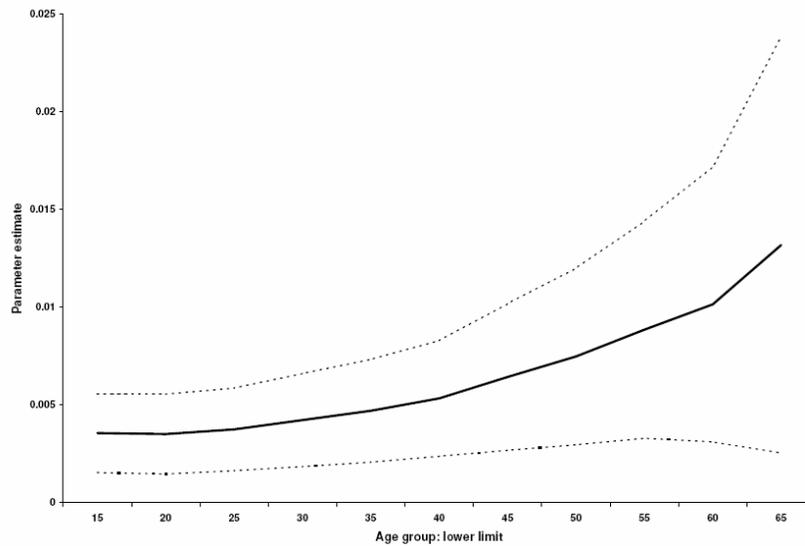
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Figure 6. Estimates of the absorption parameter: Non-OECD sample.

Conclusions

We present a new dataset of education by age group for 120 countries. This dataset has been developed using demographic back-projection methods reflecting different mortality levels for different education groups. This results in the first consistent dataset to provide full educational attainment distributions by five-year age groups for a large number of industrialized and developing countries.

Using this unique dataset, we give evidence of the importance of considering the demographic dimension of human capital in two different empirical applications. On the one hand, we show that the differences in the education level of the younger age groups explain the observed differences in GDP per capita across countries significantly better than aggregate measures of human capital which account for the full adult population. On the other hand, we present evidence on the relevance of the education levels of younger workers for technology absorption in developed economies.

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