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Measuring the effect of health on cross-country income variability

Christiano Coelho
Ibmec/RJ and Uerj

Pedro Gesteira
PPGE/UFRJ

Abstract

We construct a human capital series adjusted for measures of health based on a new dataset from World Bank for a large sample of countries. We show that the health-adjusted series of human capital increases the explanatory power of factor inputs by seven percentage points in explaining cross-country income variability, which represents 35% of the variation generated by human capital. This result shows the importance of measures of health in human capital. It is robust to changes in the sample of countries and to how we measure the schooling component of human capital.

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Contact: Christiano Coelho - christiano.arrigoni@gmail.com, Pedro Gesteira - pedro.souza@ppge.ie.ufrj.br.
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1. Introduction

Caselli (2005) shows that the previous development accounting literature established that 50% of cross-country income variance could be explained by factor accumulation. Then, he updated the calculations with 1996 data and concluded that only 39% of cross-country income variance could be explained by factor inputs. Areski and Cherif (2010) find that the proportion of income variability explained by factors accumulation consistently decreased between 1970 and 2000.

One problem with these calculations is that factor inputs are not necessarily well measured. In particular, the calculations cited above use a measure of human capital that depends only on the years of schooling. However, as is well established in the literature, other factors, like the level of the workers' health, can affect the level of human capital of a country. The omission of these factors could bias downward the estimation of factor accumulation contribution to cross-country income variability.

Our objective is to include a measure of health as a determinant of human capital. With this new measure of human capital, we recalculate the contribution of factor inputs to cross-country income variability using the most recent calibration for the elasticities, which affect the rate of returns of health measures, from microeconometrics literature. To implement our empirical strategy, we use a new dataset from World Bank that includes proxies for health for a large sample of countries. To the best of our knowledge, previous literature did not use a sample as large as ours (as, for example, in Weil (2007)) or did not use the appropriated calibrations for the elasticities of health measures (as, for example, in Caselli (2005)).

Our main result shows that the proportion of income variability explained by factor inputs, taking into account health as a human capital determinant, increases by seven percentage points, which represents 35% of the total variation generated by human capital.

2. Related literature

Regarding the theoretical consolidation of human capital and its use in empirical estimations, Becker (1962) was the first to formally study how the accumulation of human capital is determined. Afterwards, Mincer (1974) estimated the return of years of schooling in a way still used nowadays. Using the regression proposed by Mincer (1974), Psacharopoulos (1994) estimated the rate of return of years of schooling for OECD, for Sub-Saharan Africa and for the whole world. Hall and Jones (1999) used Psacharopoulos (1994) estimates to propose that the return of education depends nonlinearly of years of schooling.

For the relationship between health and human capital, Behrman and Rosenzweig (2004) finds that intrauterine nutrition significantly affects the wages of adults. Weil (2007) consolidates micro and macro evidence concerning the relationship between health and human capital. He finds that health is a potentially important determinant of human capital in the macro level.

Using development accounting, Caselli (2005) finds that only 39% of cross-country income variance in 1996 could be explained by factor accumulation. Areski and Cherif (2010) find that the proportion of income variability explained by factor accumulation consistently decreased between 1970 and 2000.

3. Data

We use three different sources of data: the World Bank, the Penn World Table (PWT, version 9.1) and Barro and Lee (2010). From the world bank database, we get information of the Human Capital Index (HCI), which we use to construct our measure of health. From PWT, we take the information of per worker GDP, the capital stock and a measure of years of schooling.

From Barro and Lee (2010), we gather an alternative measure of years of schooling, which we use in our robustness tests.

We use the year of 2017, which is the year that we have information of health from the World Bank database. Our initial sample has 144 countries, which we use to update the results of Caselli (2005). Our final sample, used in the main exercise, has 134 countries, and is limited by the World Bank sample. For an exercise using health as a determinant of human capital, our sample is an unprecedented large one. Finally, for our robustness exercise, we use years of schooling from Barro and Lee (2010), which contains a sample of 128 countries for the year of 2010.

We use the following variables from the PWT: *RGDPO* as income, *CN* as the capital stock, *EMP* as the number of workers. Then we define *RGDPO*/*EMP* as the income per worker and *CN*/*EMP* as the capital stock per worker. Both income and capital stock are PPP adjusted.

For the updated results of Caselli (2005) in section 4.1, we use the human capital from PWT, the variable:

$$HC_1 = e^{\phi(s)} \quad (1)$$

Where $\phi(s)$ is the rate of return of schooling and s are the years of schooling, and $\phi(s)$ is calculated using the results of Psacharopoulos (1994) as is showed below:

$$\phi(s) = \begin{cases} 0{,}134 \cdot s, & s \leq 4 \\ 0{,}134 \cdot 4 + 0{,}101 \cdot (s-4), & 4 < s \leq 8 \\ 0{,}134 \cdot 4 + 0{,}101 \cdot 4 + 0{,}068 \cdot (s-4), & s > 8 \end{cases} \quad (2)$$

For the main exercise, in section 4.2, which used health as well as years of schooling as determinants of human capital, we opt not to use the whole measure of human capital of the World Bank, given that it uses years of schooling of people who are between 10 and 17 years old. Instead, we use only its health measure, and we get the rate of return of years of schooling from the PWT applying the natural logarithm on HC_1. We then combine the rate of return of years of schooling with the rate of return of health to calculate the human capital as:

$$HC_2 = e^{\phi(s)} e^{\psi(h)} \qquad (3)$$

Where $\phi(s)$ is the log of the rate of return of schooling as previously defined and $\psi(h)$ is the log of the rate of return of health, whose calculation is explained below.

In order to calculate the rate of return of health we proxy the latent variable health (h) by the variables Adult Survival Rate (ASR) and the rate of bad nutrition (NUT). Albeit Weil (2007) uses adult height and age at menarche as proxies for health, we chose not to do so for the following reasons.

Although adult height data has become available to a fair number of countries, adult height variation between countries can be partially determined by genetic differences (Kraay, 2018). Moreover, the health environment in which an adult lives may be substantially different from the one in which he or she grew up, since height is almost entirely established by the time a person is in his or her mid-twenties (Weil, 2007).

Regarding age at menarche, Weil (2007) poses relevant issues about this measure: "Despite these efforts, there remain several problems with the menarche data. Some come from surveys that are not nationally representative, examining women from a few regions, or from the national capital and its environs, for example. There are also cases where the data refer to the median rather than the mean age. Finally, data are from years ranging as far back as 1957, although the vast majority are from the 1980s and 1990s".

Nevertheless, given the time of publication of Weil (2007), we have searched for more comprehensive datasets of age at menarche. The search was fruitless, as we had no luck finding one dataset available to a similar number of countries such as our sample number or one available in a compatible time span for our exercise.

For these reasons, we have decided to use the adult survival rate (ASR) and the rate of bad nutrition (NUT) as health measures. ASR is defined by the fraction of children that are 15 years old who would survive until 60 years old, and NUT is defined as the fraction of children under 5 years old who are two standard deviations below the average height, being the average and standard deviation defined by the World Health Organization (WHO). Both variables are available in the World Bank HCI database.

In order to calculate $\psi(h)$ we have to calibrate the rate of returns of ASR and NUT. Weil (2007) calculates the impact of ASR on height and uses the rate of return of height on wages to estimate the rate of return of ASR on wages. Weil (2007) finds that the impact of ASR on wages is 0.65, which means that an increase of the latent health of a country which increases ASR in 0.1 increases worker productivity in 6,5%.

Kraay (2018), using previous results of Galasso and Wagstaff (2016), obtains a rate of return of good nutrition of 0,102. So, a marginal decrease of the rate of bad nutrition (or a marginal increase in the rate of good nutrition) increases the average height on 0,102 cm. Taking account the rate of return of height on wages, he estimates that the semi-elasticity of "bad" nutrition on wages is -0.35. Therefore, an increase in the latent health of a country which decreases the rate of bad nutrition in 0.1 (or increases the rate of good nutrition in 0.1) increases the productivity of the average worker in 3.5%.

In the end, the formula we use for $\psi(h)$ is:

$$\psi(h) = \gamma(ASR, NUT) = \frac{0.65ASR + 0.35(1 - NUT)}{2} \quad (4)$$

In the robustness section 4.3 we use a third measure of human capital, based on data of years of schooling of adults of Barro and Lee (2010), which is the gross data used to construct the human capital index of the PWT. We use the rate of return of years schooling as proposed by Kraay (2018), which reviewing the literature of the theme concludes that 8% per year would be the ideal. Therefore, our third measure of human capital is:

$$HC_3 = e^{0.08s} e^{\frac{0.65ASR + 0.35(1 - NUT)}{2}} \quad (5)$$

3. Empirical Strategy

In this section we explain the methodology used to decompose the variability of income per worker between countries that is known as development accounting. Following Caselli (2005), we define a per worker production function as follows:

$$y = A y_{KH} \quad (6)$$

Where $y_{KH} = k^{\alpha} h^{1-\alpha}$, in which k is the capital stock per worker and h is the human capital per worker. As previously explained, in our update of Caselli (2005), $h = HC_1 = e^{\phi(s)}$ and in our main exercise, $h = HC_2 = e^{\phi(s)+\psi(h)}$. The variable y_{KH}, which is a composite of physical and human capital per worker, is called factors inputs. Equation (6) is called unique factor model in the literature.

The exercise question is: how effectively the unique factor model can "explain" the income variability observed in the data? To answer this question, we compare the observed variance of y_{KH} with the observed variance of y.

Following Caselli (2005), we define two measures of success, S1 and S2. To construct the first measure of success, S1, from equation (6) we use the following decomposition of the variance of the natural logarithm of y:

$$var[log\ (y)] = var[log(y_{KH})] + var[log(A)] + 2cov[log(A), log(y_{KH})] \qquad (7)$$

If all countries had the same level of productivity A, then $var[log(A)] = cov[log(A), log(y_{KH})] = 0$ and all variance of y would be "explained" by y_{KH}. Using this reasoning we define the first measure of success, $S1$, as:

$$S1 = \frac{var[log(y_{KH})]}{var[log\ (y)]} \in (0,1) \quad (8)$$

Therefore, S1 measures the fraction of variance of y "explained" by factors of production y_{KH}.

However, S1 is also subject to variations caused by *outliers* present in the database. For example, countries who have y (y_{KH}) much higher or lower than the average. In order to minimize this effect, we also work with a second measure of success, called S2, which is the inter-percentile differential defined as:

$$S2 = \frac{y_{KH}^{90}/y_{KH}^{10}}{y^{90}/y^{10}} \qquad (9)$$

Where x^p is the *p*-percentile of a given frequency distribution of *x*. Therefore, S2 compares the ratio between the ninetieth and tenth percentile of y_{KH} and y in a hypothetical situation in which the countries have the same level of technology.

4. Results

4.1 Benchmark results

Our benchmark estimates use the human capital measure of the PWT (which does not take into account health measures). In this case, we have $var[log\ (y)] = 1.25$ and $var[log\ (y_{KH})] = 0.36$, which generates S1 = 0.28.

For S2, we calculate y_{KH}^{90}/y_{KH}^{10} dividing the value of y_{KH} from United Arab Emirates (UAE), the 90 percentile, by the value of y_{KH} from Togo, the 10 percentile. The result is 4.79. For the ratio y^{90}/y^{10}, we divided the values of y from Belgium, the 90 percentile, and Nepal, the 10 percentile, which result is 19.17. With the previous results we have S2 of 0.25. [1]

These results show that a small part of income variance is explained by factor inputs, being the rest, much more than 50% in the two measures, being explained by total factor productivity (TFP). Comparing our results with those in Caselli (2005), while our S2 measure is the same, our S1 is much lower (0.28 against 0.35)[2].

However, this difference in S1 is expected if we take account the results of Arezki and Cherif (2010). These authors make a similar exercise as Caselli (2005) and conclude that the

[1] Alternatively, similar to Caselli (2005), we calculate another measure of success, S3, adding to the numerator of S1 the covariance between factors and productivity, in a way that the contribution of the covariance in equation (5) is equally divided between factors and productivity. Caselli (2005) also considers this measure and as like him, we obtain a value larger than S1. As the covariance is 0.28, we obtain S3 = 0,51, which means that, since the covariance is positive, S3 gives a larger role to the factors than S1.

[2] It is important to note that there are some differences in our sample period, sample of countries and variable construction when compared to Caselli (2005). In principle, this could explain part of the differences between both results.

explicative power of TFP consistently increases between 1970 and 2000, which implies in a consistently decrease of S1 and S2 in this period. Our results point that, at least for S1, this trend continues when we update the results with data of 2017.

Following Caselli (2005), we split the sample between members and not members of OECD and countries above (or below) the median income. The results are on table 1 below.

Table 1 – Different samples and S1

	OCDE	Non-OCDE	Above Median	Below Median
Sample size				
This work	16	128	72	72
Caselli (2005)	24	70	47	47
S1				
This work	0.20	0.28	0.38	0.34
Caselli (2005)	0.61	0.36	0.62	0.41

Elaboration: The authors.

We can see that the decrease of S1 also occurs in the subsamples, which shows that TFP has a larger role in the subsamples too. Other interesting result is the low level of S1 in the members of OECD (S1 = 0.20).

4.2 Results adding a health measure

We use Weil (2007) as a benchmark for the results we find in this section. He made a similar exercise of development accounting using only *ASR*, a sample of 92 countries and the year of 1996. His results show that the fraction of income variance "explained" by productivity drops from 59.8% to 52.9% when he includes his health measure, which suggests that the inclusion of health in human capital has a good potential in increasing the role of factor of production.

In this section, we will include health as a determinant of human capital as explained in the section 3. There are two novel contributions in our measure compared to Weil (2007). First, besides ASR, we use NUT as a determinant of health, which is supported by the previous microeconometrics literature (Behrman and Rosenzweig (2004)). Second, since we are using the World Bank database, we can work with a larger sample compared to that used by Weil (2007) (134 countries against 92 in Weil (2007)).

Using the success measures S1 and S2, for our sample of 134 countries we find that $var[log\ (y)] = 1.25$ and $var[log\ (y_{KH})] = 0.44$. So, we have S1 = 0.35.

For S2, we calculate y_{KH}^{90}/y_{KH}^{10} dividing the values of y_{KH} of UAE (the 90th percentile) and Togo (the 10th percentile), and the result is 4.38. For y^{90}/y^{10}, we divide the income of Belgium (the 90th percentile) by Nepal (the 10th percentile), obtaining 17.27. So, our S2 is 0.28.

The results of this section compared with those of the previous one are summarized on Table 2:

Table 2 – Results adding health to human capital

	HC with schooling	HC with schooling and health
S1	0.28	0.35

S2	0.25	0.29

Elaboration: The authors.

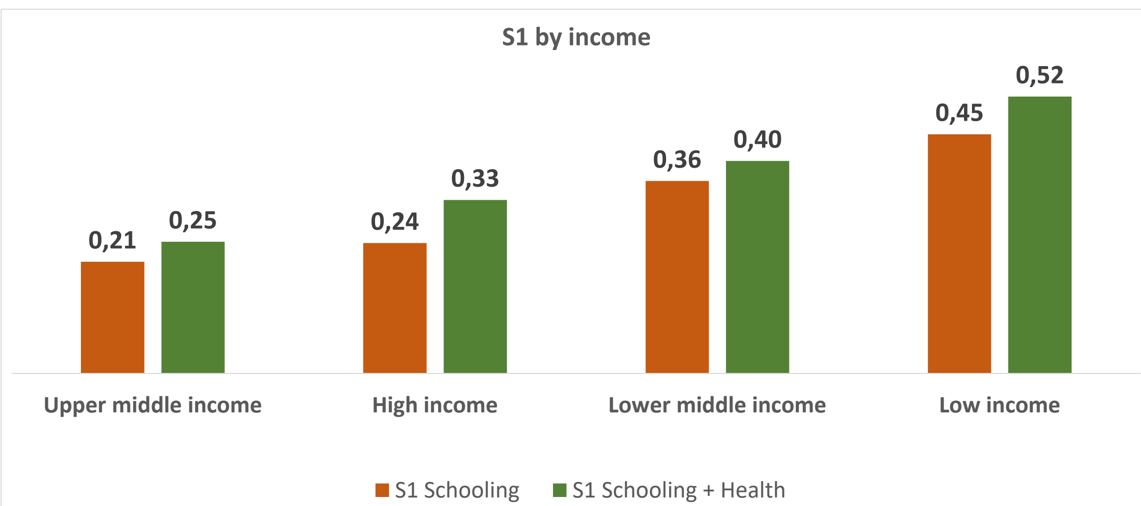
From table 2, we can see a large increase in S1, of seven percentage points, which suggests that health is an important determinant of human capital helping to improve the explaining power of factor inputs. Comparing our results with a model with only capital as input, S1 increases from 0.15 to 0.35, a 20-percentage points variation. As shown in the table 2, the health component explains 7 out of 20 percentage points, which represents 35% of the total variation generated by human capital. This result shows that health is quantitatively important as a component of human capital.

4.3 Robustness

4.3.1 – Analyzing subsamples

To test the robustness of our results we divide our sample in subsamples according to the level of income, geography, if the country is member of OECD and if the country income is above or below the median income. Results for the division by income are on graph 1 below:

Graph 1 – S1 by income

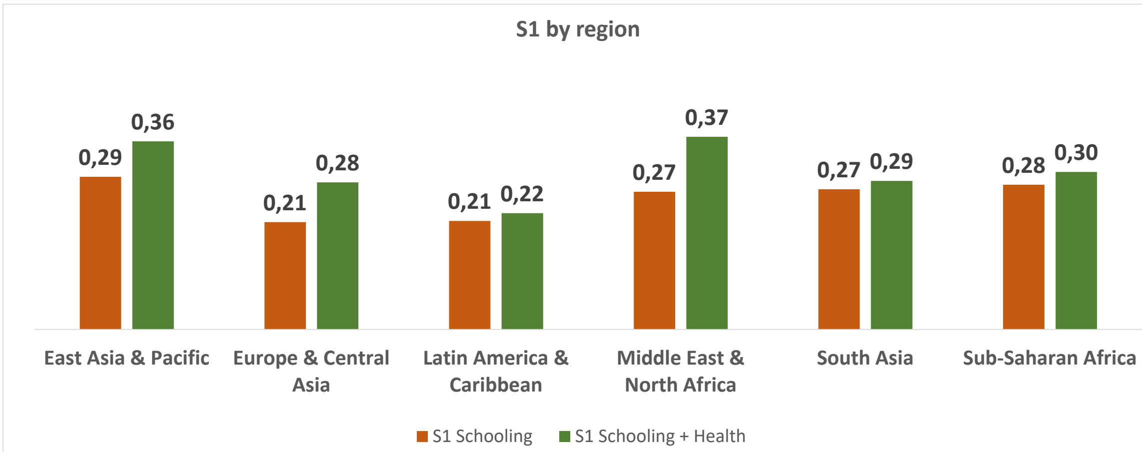


Elaboration: the authors

We can see from the graph 1 above that for all groups the S1 measure increases after the inclusion of health as a determinant of human capital. The groups with the larger increases were the high income, with an increase of 9 percentage points and the low income, with an increase of 7 percentage points.

Results for subsamples according to geographic regions are on graph 2 below:

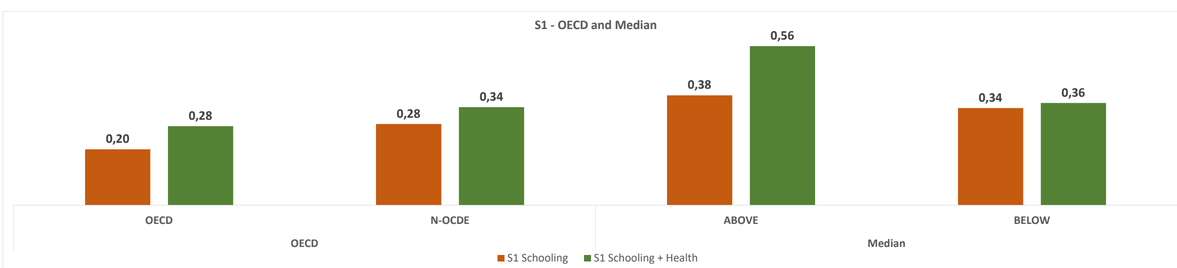
Graph 2 – S1 by region



We can see from the graph 2 above that for all groups the S1 measure increases after the inclusion of health as a determinant of human capital. The groups with the larger increases were East Asia and Pacific, Europe and Central Asia, both with an increase of 7 percentage points, and the Middle East and North Africa, with an increase of 10 percentage points.

Results for subsamples according to membership of OECD and median income are on graph 3 below:

Graph 3 – S1 by membership of OECD and above/below median income



We can see from graph 3 the same pattern of graph 1: for high-income countries (OECD and above median) the S1 measure increases substantially (8 percentage points for OECD and 18 percentage points for countries above the median). However, for countries relatively poor, nonmembers of OECD and below median, the increases in S1 were smaller (6 percentage points for nonmembers of OECD and 2 percentage points for countries below the median).

4.3.2 – Using an alternative measure of human capital

In this section, we use human capital adjusted for health measures using an alternative measure of schooling. For this, we use the Barro and Lee (2010) database and a linear rate of return of schooling of 8%, as proposed by Kraay (2018). Therefore, we use equation (7) to calculate the human capital. When we use the database of Barro e Lee (2010), our sample decreases from 134 to 128 countries.

Using $HC3$, we have $var[log\ (y_{KH})] = 0.39$ and $var[log\ (y)] = 1.20.$ Using these numbers we have S1 = 0.33. Comparing with the estimate of the section 4.2 (S1 = 0.35), we have a decrease of 2 percentage points, but compared with S1 without health we still have an increase in S1 of 5 percentage points.

5. Conclusion

We construct a human capital series adjusted for health measures based on a new dataset from the World Bank for a large sample of countries. Besides, we calibrate the elasticities of health measures using the most recent results of microeconometrics literature. With this new series of human capital, we recalculate the contribution of factor inputs to cross-country income variability.

Our main result shows that the proportion of income variability explained by factor inputs, taking into account health as a human capital determinant, increases by seven percentage points, which represents 35% of the variation generated by human capital. Our results are robust to changes in the sample of countries and to a different measure of the schooling component within the human capital series.

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