WPS8590

Policy Research Working Paper 8590

Background Paper to the 2019 World Development Report

The Effect of Increasing Human Capital Investment on Economic Growth and Poverty

A Simulation Exercise

Matthew Collin
David Weil

WORLD BANK GROUP
Human Development Vice Presidency
Office of the Chief Economist
September 2018

Abstract

This paper examines the dynamic responses of income and poverty to increased investment in the human capital of new cohorts of workers, using a quantitative macroeconomic model with realistic demography. Compared to a baseline in which the rate of human capital investment currently observed in every country remains constant, the paper examines two alternative scenarios: one in which each country experiences a rate of growth of human capital investment that is typical of what was observed in the decade ending in 2015, and one in which each country raises human capital investment at a rate corresponding to the 75th percentile of what was observed in the data. In the former, world GDP per capita is 5 percent higher than baseline in the year 2050, while the global rate of $1.90 poverty is 0.7 percentage points lower in that year. In the latter, world GDP per capita is 12 percent higher than baseline in 2050, while the rate of $1.90 poverty drops by 1.4 percentage points. These gains are concentrated in poor countries. The paper argues in the context of our model that investing in people is more cost effective than investing in physical capital as a means to achieve specified income or poverty goals.

This paper—prepared as a background paper to the World Bank's *World Development Report 2019: The Changing Nature of Work*—is a product of the Office of the Chief Economist, Human Development Vice Presidency. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://www.worldbank.org/research. The authors may be contacted at mcollin@worldbank.org and david_weil@brown.edu.

The Effect of Increasing Human Capital Investment on Economic Growth and Poverty: A Simulation Exercise

Matthew Collin*
World Bank

David Weil†
Brown University

Keywords: Human Capital, Economic Growth
JEL classification: I10,I20,O4

*Email: mcollin@worldbank.org, Thank you to Aart Kraay, Roberta Gatti, Ritika Dsouza, Nicola Dehnen, Maria Ana Lugo and Daniel Mahler for helpful comments, suggestions and access to data.
†Email: david_weil@brown.edu

1 Introduction

Gaps in human capital investment rates between countries are very large. These gaps are most easily visible in the the standard metrics used to assess human capital, such as school attendance rates and the highest grade completed among the working age population. More recently, economists have broadened the measures used to assess human capital investment to include test scores, as a measure of school quality, and health inputs and outcomes, as measures of the physical abilities of workers. Not surprisingly, examination of these extended measures of human capital investments shows that differences between countries tend to be even larger that had previously been thought: on average, children in poor countries not only receive fewer years of schooling, but the schooling that they do receive is of lower quality, and they enter the labor force less healthy than their contemporaries in rich countries.

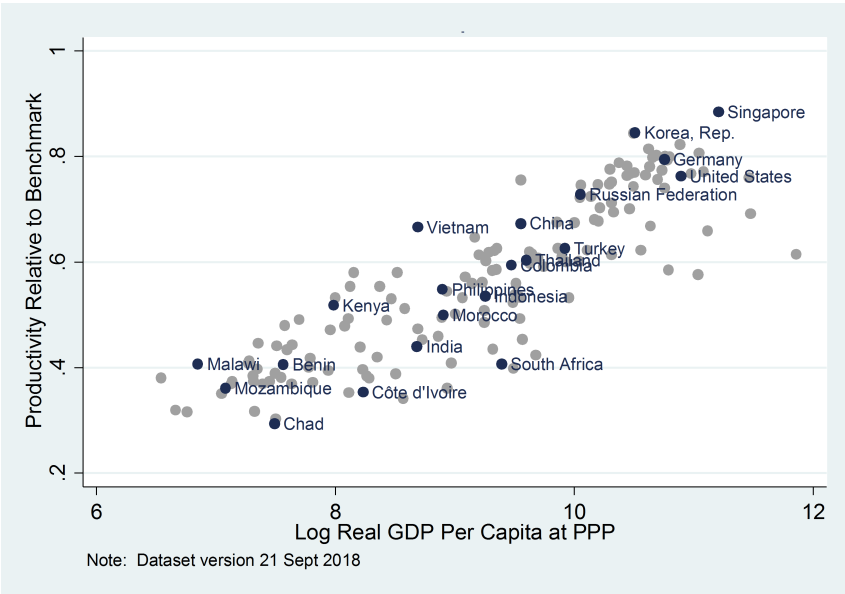
A recent World Bank project (see Kraay (2018)) has produced the Human Capital Index (HCI), a new measure of the flow rate of human capital investment across countries. The HCI incorporates data on school attendance rates, test scores, and health (combining adult health, as measured by survival rates, with child stunting and mortality). Following Weil (2007), the weightings of the different components of the HCI are based on evidence of effects of schooling and health on wages, along with an assessment of the mapping from test scores into school-year equivalents. The measure applies to investments through the end of the period of secondary schooling. The data are scaled so that a value of 1.0 would represent a country in which there was no childhood or working age mortality, no stunting, all children received a complete secondary education, and test scores were equivalent to the 625 on the PISA scale.

Figure 1 shows the relationship between the HCI and GDP per capita. Values of HCI range from between 0.8 and 0.9 in the highest investing countries to between 0.3 and 0.4 in the lowest. Not surprisingly, there is a tight correlation between income and human capital investment. There are also some interesting outliers: China and Vietnam have unexpectedly high HCI given their levels of income, while a number of oil producers (not highlighted) have unexpectedly low levels.

The high correlation of HCI and income reflects causality flowing in both directions: human capital contributes to the production of output, and richer countries can afford to invest more in their children. The correlation also reflects the impact of other factors, such as the quality of institutions, that affect both income and human capital investment. Thus one cannot simply use the slope of the curve in Figure 1 to answer causal questions about HCI and income. Rather, answering questions like this requires a model that incorporates well identified estimates of the effect of human capital on output.[1]

[1] Related literature using the technique of development accounting (see Caselli (2005) for a summary) addresses the question of how much of the cross-country variation in income is explained by variation in human capital. Weil (2007) expands the framework to take into account cross-country differences in health. Schoellman (2011) includes a measure of educational quality in development accounting, although rather

Figure 1: The human capital index



Source: reproduced from Kraay (2018)

From the perspective of an individual country, the most interesting question is how much higher income would result from a given increase in human capital investment. As shown in Kraay (2018), the answer to this question in steady state is very simple: because the HCI measures worker productivity relative to the maximum, the increase in income per capita is proportional to the rise in the HCI. Thus, for example, a country that raised its HCI from 0.5 to 0.75 would see a 50% increase in income per capita relative to what it would have been if human capital investment had remained constant.

While the increases in steady state income resulting from increased human capital investment are large, they also come with a significant time delay, which has to be taken into account in any evaluation of their desirability. The most obvious source of this delay is that HCI measures the level of investment[2] being applied to the current generation of young people, while the labor force itself is composed of people who received their human capital investments at various times in the past. It will take more than four decades – the time between when people enter the labor force and when they leave it – for an increase in the HCI to be fully reflected in the human capital of workers. In addition, there is an follow-on effect from higher human capital investment, via the accumulation of physical capital, to higher output. This, too, takes time to fully play out. Assessing these effects thus requires a more elaborate dynamic model, as in Ashraf, Lester, and Weil (2008).

than using test scores as in Kraay (2018) he uses the wages of immigrants into the United States. (Caselli 2016) does a development accounting exercise for Latin American countries using school attainment, school quality, and health.

[2]In this paper, we refer to investment to indicate changes in the level of human capital, not spending on human capital.

Beyond tracking the evolution of GDP per capita in response to changes in HCI, we put the model we construct to two additional uses. First, we extend the existing literature by looking explicitly at how poverty rates evolve over time in response to changes in HCI. Second, we use the model to compare changes in output and poverty generated by changing HCI to those that would be generated by changes in the rate of investment in physical capital.

Our starting point for this exercise is information on the demographic structure of the population: how many people there are in each age group (specifically, we break down the population into five-year age categories). The United Nations Population Division collects this data, and also makes forecasts of demographic structure going forward, which we incorporate into our model.

We combine this demographic data with information on the educational attainment of the population, also broken down by five year age groups (Barro and Lee 2013), augmented by IHME (2015). Having age-specific data on educational attainment is important because as time goes by, older cohorts, which tend to have lower educational attainment, will be replaced in the labor force by younger, more educated cohorts, a process that will automatically raise the average level of schooling in the population.[3]

Combining data on population age structure and educational attainment of different age cohorts, we can calculate the average level of human capital per working age adult, which is one of the inputs into production in the economy. We can also measure countries stocks of physical capital (the other key input into production). Within our model we can track the amount of physical capital evolves over time, under the assumption that the investment rate stays fixed at is current level. With data on both human and physical capital, as well as GDP per worker, we can also calculate a measure of total factor productivity in every country. Finally, knowing the ratio of working age adult to the population as a whole, we can track how production per worker is translated into production per capita.

With all of these pieces in place, we can construct scenarios laying out how the standard of living in a country will change over time under different assumptions of the value that HCI will take. Our particular interest is in how changing the HCI from its current level will play out in terms of income and poverty. To do this analysis, we start by constructing a baseline scenario of how the economy will develop if the current level of HCI is maintained into the future. Along this baseline path, growth and poverty reduction occur for four reasons. First, as mentioned above, the current HCI in most countries represents a higher level of investment than was received by older cohorts of workers. Thus the process of aging and labor force replacement will naturally raise the average level of human capital per worker. Second, the ratio of working age to total population is forecast to change in response to past (and forecast) variations in fertility. In many developing

[3]Ideally, we would like to have similar data on school quality and childhood health inputs by age cohort. Unfortunately, such data are not available.

countries, this demographic dividend will be of significant magnitude. Third, we expect productivity to grow going into the future, as it has historically. Finally, the level of physical capital will adjust, in particular growing in most countries as productivity and human capital per worker increase.

Moving from forecasts of income per capita to forecasts of the poverty rate requires some additional machinery. Poverty is a function of both the average level of income and how income is distributed among households. For example, in a country where average household income is above the poverty threshold, a higher level of income inequality will imply that the fraction of households that are poor will be higher. Inequality is measured by the Gini coefficient, for which the World Bank has an estimate for every country in our sample. In forecasting future poverty, in both our baseline and alternative scenarios, we assume that the Gini coefficient in each country remains constant at its most recently observed level.

To assess the effect of increased HCI, we compare the changes in income and poverty that would result from a particular policy (which we call an alternative scenario) to the changes in those same measures that would occur in the baseline scenario just described. Income rises and poverty falls in the baseline scenario. By looking at how the alternative scenario differs from the baseline, we don't inadvertently give credit to a particular policy innovation for changes in income and poverty that would take place anyway.

We consider three alternative scenarios. As described in greater detail below, two of these scenarios are based on data on how HCI levels have increased over the period 2005-2015 in the subset of countries for which such data are available. The first observes how the gap between the HCI and the maximum of 1.0 has changed for the median country in our data that has seen with improvements in each of the underlying components of HCI. We then apply this rate of change in the gap to all countries in our simulation. This corresponds to countries closing the gap between their current levels of HCI and the maximum of 1.0 at a rate of approximately 4% every five years. In this scenario, the typical developing country, with an HCI of 0.5 in 2015, would see this value rise to around 0.62 in 2050. The second scenario more optimistically assigns to each country the rate of improvement in each component that is the 75th percentile of what was observed, which corresponds to a country closing 9% of the gap between its current HCI and the maximum of 1.0 every five years.

To give a flavor of the results, we find that in the first of these alternative scenarios, GDP per capita in the world as a whole would be 5% percent above its level in the baseline scenario in the year 2050, and among the low and lower-middle income countries (what we will call developing countries), the increase would be 9%. The poverty rate - the percentage of those living on less than $1.90 a day - would similarly be 0.7 percentage points lower by 2050 than it would along the baseline scenario (1.2 percentage points in developing countries). Another way to assess effect of this policy is by looking at the year by which a particular poverty target is reached. For example, for the policy just

described, developing countries as a whole would reach a 5% poverty rate between 2045 and 2050, as compared to between 2050 and 2055 in the baseline scenario.

In addition to the two scenarios just described, we also include results from a more dramatic policy in which every country in the world were to instantaneously (as of the year 2020) raise its level of HCI to the highest possible level, that is, 1.0 on the scale described above. This scenario is not meant to be realistic, but rather included solely as an aid to understanding the dynamics of the model. In this case, worldwide, the poverty rate in the year 2050 would be 2.5 percentage points lower than it would be in the baseline scenario.

Although focus on reporting results for large groups of countries, the model that we have constructed in fact examines the data on a country-by-country basis. In this context, it can be used for planning and assessment: What dividends will be reaped by a particular increase in HCI, and when will they arrive? What path of changes in HCI is required to hit a particular target?

Of course, the output of our simulation model, as with any such model, is subject to a fair bit of uncertainty. Some of this uncertainty has to do with the baseline scenario itself. We build into the baseline scenario assumptions about future demographic change, the investment rate, and productivity growth, all of which might turn out to be wrong. However, because our main interest is in evaluating the effects of particular policies, and because our methodology compares alternative and baseline scenarios which use the same assumptions about future values of these non-policy variables, errors in our forecasts of these variables largely cancel out. A more serious source of potential error in our assessment of policies is if we have not included all of the different pathways by which HCI affects income growth and poverty. One pathway that we have not included is the effects of parental human capital on fertility and on children's human capital. More educated parents tend to have lower fertility and also to invest more in their own children's education. They are also more capable of making decisions that positively affect child health. All of these effects would raise the increment to output per capita, and similarly the reduction in poverty, that would result from a given increase in HCI. A second important pathway by which an increase in HCI would affect poverty is by changing the distribution of income. In our simulations, we assume that that the level of inequality in a country (the Gini coefficient) would be the same in the alternative scenario as in the baseline scenario. Realistically, however, increases in HCI are likely to raise the human capital of poor people more than that of rich people, simply because the former group has a much larger deficiency to be addressed. A more equal distribution of human capital would in turn be expected to reduce inequality, and thus to reduce poverty by even more than we are accounting for in our alternative scenarios.

2 Model Specification

In this section we describe in more detail the model we use to simulate the effects of human capital improvements on economic growth and poverty reduction. The model uses standard components. We assume output is produced in a Cobb-Douglas production function using physical capital and quality-adjusted labor as an input. The growth rate of total factor productivity, representing technological change and the efficiency of institutions, is taken as exogenous and constant. We also take forecast demographic changes as exogenous and invariant to the changes in human capital investment that we consider.

The innovations in the model come in the calculation of quality-adjusted labor input, that is, in looking at the effect of human capital investments on how much labor workers can supply. We follow the methodology and parametrization of Kraay (2018) in using data on years of education, school quality, and health outcomes to construct measures of human capital for new cohorts of workers, and then track the human capital of the aggregate labor force as cohorts of new workers replace the older ones. As discussed in more detail below, we also translate changes in output per worker into per-capita income changes, and use these to track the effect of growth on poverty.

2.1 Basic Assumptions

Time, denoted as t, proceeds in five year increments. Our model will be calibrated for 2015, when $t = 0$, then $t = 1$ will indicate 2020, and so on.

While working ages can vary across contexts, in the model we treat all individuals aged 20-64 as being members of the labor force. For many developing countries, fifteen would be a more appropriate age for the start of labor force participation. However, the education data we rely on includes schooling up through the 12th grade, which typically ends at the age of eighteen. We thus begin the analysis at the age of twenty in order to capture all gains in secondary school attainment measured in the Barro-Lee data. We assume all individuals fully participate in the labor force during these ages, regardless of gender or age. Furthermore, we do not make any adjustment for people being out of the labor force while receiving education after the age of twenty, or for their being in the labor force prior to this age.

We will denote population in five year age bins (20-24, 25-29...). Age is denoted a. We will index age groups by the first age of the bin, i.e. $a = 20, 25$, etc.

Throughout the simulation, we take as given age-specific population totals by five year age groups from World Population Prospects: The 2017 Revision (United Nations Department of Economic and Social Affairs, Population Division 2017). Population projections are treated as exogenous: we do not allow for feedback from human capital (or income) to fertility, mortality, or labor force participation. We also do not allow for differential mortality by education.

For education, we look only at data on attainment through secondary school. We

do not include tertiary education.[4] Implicitly, differences in tertiary education among countries will be captured in the productivity term, and will be assumed to be unchanging through the simulation.

In this paper, we assume that the level of human capital observed in 20-24 year olds in 2015 corresponds to that which would be produced by the human capital investment flow which is measured by the Human Capital Index.

For the purpose of calculating changes in human capital, capital, productivity, GDP and poverty, we will analyze countries individually. Later on, we will aggregate these results to consider the effects for different country income groups or for the world. For our calculations below, we will not use country subscripts.

2.2 Calibration for $t = 0$

For calibration the model for the first period, we rely on 2015 data where possible. When it is not available we use the nearest available year. Below we describe how this data is used to generate starting values for the model.

Population by age and Working Age Population

Let $P_{a,t}$ be the number of individuals (combining both sexes) in age group a in year t. We define the Working Age Population as

$$WrkAge_t = \sum_{a=20}^{60} P_{a,t} \tag{1}$$

And the fraction of the Working Age Population as

$$WrkAgeFract_t = \frac{WrkAge_t}{\sum_a P_{a,t}} \tag{2}$$

Gross Domestic Product

For GDP, we use the World Bank's measure of GDP in 2015, measured in constant 2011 international dollars at purchasing power parity (PPP). Let this measure be GDP_0. We then defined GDP per worker as

$$GDPperWorker_0 = \frac{GDP_0}{WrkAge_0} \tag{3}$$

And GDP per capita as

$$GDPperCapita_0 = GDPperWorker_0 \times WrkAgeFract_0 \tag{4}$$

[4]The only exception is the smaller subset of countries for which we rely on the Institute of Health Metrics and Evaluation (IHME)'s measure of years of schooling, which includes pre-primary and tertiary schooling. We discuss how we account for this in Appendix 1.

Physical Capital Stock

Total capital at time zero is defined as K_0 . Our source is the Penn World Tables 9.0, from which we use a country's 2014 value of capital stock at current PPPs in millions of 2011 $US. We then define capital per worker as:

$$KperWorker_0 = \frac{K_0}{WrkAge_0} \tag{5}$$

Education Attainment

We obtain data on educational attainment each five year age group from two sources. The first is Barro-Lees database of educational attainment, which covers 146 countries up to the year 2010, and is disaggregated both by sex and by five-year age groups (Barro and Lee 2013).

For our estimates of 2015 educational attainment, we assume each age group retains the value it would have had five years previously - that no cohort obtains any further years of schooling following 2010. For example, we assume the 35-39 age group has the same educational attainment as the 30-34 age group did in 2010. As not everyone in the 2015 20-24 age group would have completed their secondary schooling in 2010, we assign the 2015 20-24 age group the same value as the 2010 20-24 age group. We restrict educational attainment to primary and secondary schooling only. For the small subset of countries that have combined primary and secondary schooling attainment greater than 12 years, we cap these values at 12.

Barro-Lee data is unavailable for 75 countries in our dataset. For these, we use data on educational attainment from estimates produced by the Institute of Health Metrics and Evaluation (IHME 2015). IHME's data does not distinguish between different levels of schooling. We convert IHME years of schooling into Barro-Lee Primary and Secondary schooling equivalents using a method described in Appendix 1. As with the Barro-Lee data, we cap average years of schooling at 12 years.

Define $EA_{a,t}$ as the average number of years of primary plus secondary school of individuals in age group a in year t. For the calculations below, we will take the theoretical maximum of this measure to also be 12.[5]

Education Quality

Data on educational quality is more sparse than that of attainment. Where attainment data is available for older cohorts, data on the quality of education covering all the age-bins

[5]Note that this treatment of educational attainment differs from that in the Human Capital Index, which uses UNESCO methodology to calculate Expected Years of Schooling (EYS), based on a total potential 14 years of schooling pre-primary through 12th grade. To deal with that mismatch, in the sections below we will scale up educational attainment proportionally to the change in EYS.

in our data is rarely available, particularly for developing countries infrequently subject to testing.

We thus assume that all cohorts at time zero have the same quality of education, even if they differ in their attainment, so that

$$EQ_{a,0} = EQ_0 \forall a \tag{6}$$

EQ_0 in each country is assigned based on data on the most recent available observation of harmonized test scores from Altinok, Angrist, and Patrinos (2018). These are in "PISA-equivalent units." Defining the most recent test score as $Score_0$, we convert it into a quality measure using the methodology of Angrist, Filmer, Gatti, Rogers, and Sabarwal (2018).

$$EQ_0 = 1 - \Psi \times (\frac{625 - Score_0}{625}) \tag{7}$$

Where we set $\Psi = 1$, which is consistent with the findings of that paper.

Adjusted Years of Education and Human Capital from Education

Quality adjusted years of education for all age cohorts at time zero are calculated by multiplying their years of schooling (adjusted as described above) by the time-zero quality measure, specifically

$$AdjEd_{a,0} = EA_{a,0} \times EQ_0 \tag{8}$$

Finally, human capital from education (scaled to be 1 in the theoretical maximum country) is constructed for each age group at time zero as

$$HCSchool_{a,0} = e^{(\phi \times (AdjEd_{a,0} - 12))} \tag{9}$$

Where ϕ is the Mincerian return to human capital, assumed to be .08.

Health and human capital from health

As with education quality, we are unable to separately determine the health status of different age bins in our data. This would require finding childhood health inputs for currently middle aged workers at the time when they were young. Instead, we rely on the two contemporaneous health measures used in the HCI, the proportion of children who are stunted and adult survival rates (ASR), and apply them to the entire adult population. Our two input measures of health are ASR_t and $Stunting_t$, where the latter is not available for all countries.

Human capital from health is constructed directly from these measures. It is scaled to have a value of 1 in a country with perfect health. If both measures are present, we

construct

$$HCHealth_{a,0} = e^{\frac{(\gamma_{ASR} \times (ASR_0 - 1) - \gamma_{Stunting} \times Stunting0)}{2}} \tag{10}$$

If only ASR data are available, then we construct health human capital from just ASR, so that

$$HCHealth_{a,0} = e^{(\gamma_{ASR} \times (ASR_0 - 1))} \tag{11}$$

We use values of $\gamma_{ASR} = 0.6528$ and $\gamma_{Stunting} = 0.3468$ based on Weil (2007) and Kraay (2018).

Total Human Capital

Total human capital for an age cohort is the product of human capital from schooling and human capital from health

$$HC_{a,0} = HCSchool_{a,0} \times HCHealth_{a,0} \tag{12}$$

Total human capital for the economy is simply the sum of cohort-specific human capital multiplied by population. In practice, we only look at this in per worker terms:

$$HCperWorker_0 = \frac{(\sum_{a=20}^{60} P_{a,0} \times HC_{a,0})}{WrkAge_0} \tag{13}$$

Productivity at $t = 0$

We calculate productivity in 2015 using our measures of GDP per worker, capital per worker and human capital per worker.

$$A_0 = \frac{GDPperWorker_0}{KperWorker_0^{\alpha} \times HCperWorker_0^{(1-\alpha)}} \tag{14}$$

Where we take the base case value of $\alpha = \frac{1}{3}$

Poverty Headcount

Let $Gini_0$ be the Gini coefficient at time zero (measured on a 0-1 scale). We assume that income growth does not affect the Gini coefficient. Pov_0 is the poverty headcount at time zero (also measured as a fraction between zero and one).

We assume that household income is distributed lognormally, with μ and σ being the mean and standard deviation of the log of income. The Gini coefficient is thus given by

$$Gini = 2 \times \Phi\left(\frac{\sigma}{\sqrt{2}}\right) - 1 \tag{15}$$

Where Φ is the normal CDF. We then calculate the time zero standard deviation of the log of income, which itself is constant as a result of the Gini being held constant.

$$\sigma = \Phi^{-1}\Big(\frac{Gini_0 + 1}{2}\Big) \times \sqrt{2} \tag{16}$$

Define P as the poverty threshold. The poverty headcount at time zero is given by

$$Pov_0 = \Phi\Big(\frac{ln(P) - \mu_0}{\sigma}\Big) \tag{17}$$

Rearranging,

$$\mu_0 = ln(P) - \sigma \times \Phi^{-1}(Pov_0) \tag{18}$$

We calculate μ_t by assuming that the arithmetic mean level of household income has grown by the same proportion as GDP per capita. Let m_t be the arithmetic mean of household income.

$$\frac{m_t}{m_0} = \frac{GDPperCapita_t}{GDPperCapita_0} \tag{19}$$

From the property of the lognormal,

$$m_t = e^{(\mu_t + \frac{\sigma^2}{2})}$$

Thus

$$ln(m_0) = \mu_0 + \frac{\sigma^2}{2}$$

$$ln(m_t) = \mu_t + \frac{\sigma^2}{2}$$

So

$$\mu_t = \mu_0 + ln\Big(\frac{GDPPerCapita_t}{GDPPerCapita_0}\Big) \tag{20}$$

The expression for the poverty headcount at time t is:

$$Pov_t = \Phi\Big(\frac{ln(P) - \mu_t}{\sigma}\Big)$$

Substituting in the expressions for μ_0 and μ_t above, we calculate the poverty rate at time t as

$$Pov_t = \Phi\Big[\Phi^{-1}(Pov_0) - (\frac{1}{\sigma})ln\Big(\frac{GDPPerCapita_t}{GDPPerCapita_0}\Big)\Big] \tag{21}$$

We perform these calculations for all three prevailing poverty lines: \$1.90, \$3.20 and \$5.50 a day PPP. Data on poverty headcount ratios and Gini coefficients for each country are taken from the most recent year available from the World Bank's data (produced by PovCal).

Investment Rate

For the investment rate Inv_0, we rely on the World Bank's measure of gross capital formation as a percentage of GDP. We assume the investment rate remains constant throughout the entire scenario, and takes on the value of each country's average over the years 2006-2015.

2.3 Simulation Scenarios

For each country we have data for, we will construct several scenarios, each of which will be derived from the time paths followed by all of the endogenous variables. Each scenario will share a common rate of productivity growth, which will be taken as exogenous:

$$A_t = A_0(1+g)^{5t} \tag{22}$$

We will set $g = .013$, which is chosen so that the world poverty rate in 2030 is equal to 5.6% in the typical scenario that we discuss below. The value of 5.6% is consistent with World Bank forecasts of poverty in that year.

Baseline Scenario (Constant HCI)

We will start by constructing a path that would be followed if the investments in human capital per worker remained constant at its time zero level (the current HCI). That is, the human capital of the youngest working generation (those aged 20-24) stays fixed, and slowly the entire population takes on that same value as older generations age out of the workforce. Additional dynamics will come from productivity growth, physical capital accumulation, change in the size of the working age population, and change in the dependency ratio.

Cohort specific human capital is constructed by aging all existing working age cohorts, and then assigning to the youngest working age cohort the level of human capital from the youngest cohort at time zero.

$$HC_{20,t+1} = HC_{20,0}$$

$$HC_{a+5,t+1} = HC_{a,t} \qquad for \qquad a = 25 \ldots 60$$

$$HCperWorker_t = \frac{(\sum_{a=20}^{60} P_{a,t} \times HC_{a,t})}{WrkAge_t} \tag{23}$$

Capital evolves as follows:

$$KperWorker_{t+1} = \frac{WrkAge_t}{WrkAge_{t+1}}[KperWorker_t + 5 \times (Inv_0 A_t KperWorker_t^{\alpha} HCperWorker_t^{1-\alpha} - \delta k_t)] \tag{24}$$

We use a base case value of $\delta = .05$ for capital depreciation. GDP per worker and GDP per capita are then generated as

$$GDPperWorker_t = A_t \times KperWorker_t^{\alpha} \times HCperWorker_t^{1-\alpha} \tag{25}$$

$$GDPperCapita_t = GDPperWorker_t \times WrkAgeFrac_t \tag{26}$$

The baseline scenario is useful for understanding how, even when human capital investments remain fixed, GDP per capita and poverty would evolve solely due to older cohorts with lower levels of educational attainment ageing leaving the workforce. We next consider three alternative scenarios where the entire HCI rises at different rates over the 25 years, with varying degrees of optimism.

Scenario 1: Typical growth in the HCI

We first consider the scenario where countries experience increases in the components of human capital at the same rate as the median country did over the past decade. For this, we turn to the data underlying the HCI on expected years of schooling, harmonized learning outcomes, stunting rates and adult survival rates. For the countries that there is data for both 2005 and 2015, Table 1 displays the rate of change at the 50th percentile for each outcome separately.

We consider the collective effect of these changes at the 50th percentile would have on the HCI of a country with median levels of these outcomes in 2015. That is, what the change in the HCI would be if a country with EYS of 11.84, harmonized learning outcomes of 423.57, non-stunted rates of 0.77, and adult survival rates of 0.87 increased these outcomes by 0.482, 6, 0.051 and 0.022 respectively.

Specifically, we consider the percentage change in the "HCI gap," the difference be-

Table 1: Typical and optimistic values for changes in human capital

Outcome	Change between 2005-2015		Median value in 2015
	50th percentile	75th percentile	
Expected years of schooling	0.482	1.151	11.84
Harmonized learning outcomes	6	19	423.57
(Non) stunting rates	0.051	0.1	0.77
Adult Survival Rates	0.022	0.043	0.87

tween the average human capital of the first age bin and the theoretical maximum of 1.0, that would result from this typical increase in the components. Define $Closed_t$ as the fraction in the gap between the time zero value of the HCI and its maximum that has been closed in year t. A value of zero indicates that the country has not changed its HCI since time zero. A value of one indicates that it has moved all of the way to maximum level of HCI.

If a country with median values of the components in 2015 saw the same increases in those components as the 50th percentile country (for each component) did between 2005-2015, we would expect that country to close roughly 1% (0.0073) of the HCI gap every year, or roughly 4% (.0359) every five years.

To simulate this scenario, rather than simulate changes in all the components of human capital, we will instead apply a 4% (.0359) percentage decrease in the HCI gap for each country every five years. Thus value of $Closed_t$ determines the human capital of the youngest generation of workers, so that[6]

$$HC_{20,t} = 1 - Closed_t \times (1 - HC_{20,0})$$

Scenario 2: Optimistic Growth in the HCI

For our second scenario, we repeat the same exercise as in Scenario 1, but instead we consider the percentage change in the HCI gap that would result from a country experiencing the same increase in the HCI components as countries at the 75th percentile do. In this scenario, our hypothetical country would experience a 2% (.0194) annual decrease in the HCI gap, equivalent to approximately a 9% (.0931) decrease every five years. We take this decrease as our optimistic scenario, and thus apply a 9% decrease in the HCI gap for each country in our simulation every five years.

[6]Note that we assume that future improvements in human capital investment only affect new cohorts of workers. This assumption is clearly appropriate in the cases where the improvement takes the form of higher school quality and additional years of primary and secondary education. In the case of health, it is less clear. Improved health in the form of lower stunting clearly only affects children, but to the extent that better health is reflected in adult survival, it may indicate both more human capital investment in current young people and better health of current adults. By omitting this latter channel, we may understate the effect of health improvements on output growth and poverty reduction.

Scenario 3: the HCI moves to the frontier immediately

In this scenario, we consider the change in GDP per capita and poverty that would result from each country immediately moving to the frontier - an HCI of 1.0. In this scenario, each new 20-24 age group has human capital per worker of one, and the human capital per worker across the entire workforce slowly converges to this value as the older cohorts age out of the workforce.

While this is clearly not a plausible scenario for most countries, it is a useful exercise as it establishes an upper bound for the growth effects of improvements in human capital, as the growth effects of investments today only manifest as quickly as the workforce ages and is replaced.

3 Results

3.1 Human capital per worker, GDP per capita and poverty

Following the procedure described in Section 2, we calculate our results for 35 years into the future, from 2015 to 2050. We do so for every country in our data, then display results averaged across the entire sample, which we call "the world."[7]

Our first results are for human capital per worker, which we calculate in absolute terms for the world. In our baseline case where human capital investments remain constant, human capital per worker declines slightly over the next 35 years, from 0.58 to 0.62, driven primarily by demographic trends. Under the typical and the optimistic scenarios, human capital per worker rises modestly, from approximately 0.58 to 0.62 and 0.68, respectively. If the HCI gap was closed immediately - with all new cohorts of workers having human capital per worker of one, average human capital per worker would approach 0.92 by 2050. Due to the slow ageing-out of older workers with lower levels of human capital, under this scenario world human capital per worker would not converge to 1 until 2060.

3.2 GDP per capita

Figure 3 shows the path of GDP per capita for the baseline and three alternative scenarios that we have been considering. Under the typical and optimistic scenarios, global GDP per capita would be approximately 5% and 12% higher than the baseline by 2050. By contrast, if the HCI gap was closed immediately, GDP per capita would be 38% higher by 2050. This global view masks a good deal of heterogeneity. Gains in income would be significantly larger among poorer countries, for which initial values of the HCI are lower. For low income countries (as per the World Bank's classification), GDP per capita would be 15% higher in 2050 under the typical scenario, relative to the baseline. In the optimistic scenario, GDP per capita in this group of countries would be approximately 33% higher.

[7] Throughout the time period we consider in this paper, our results cover roughly 90-92% of the world population.

Figure 2: Human capital per worker

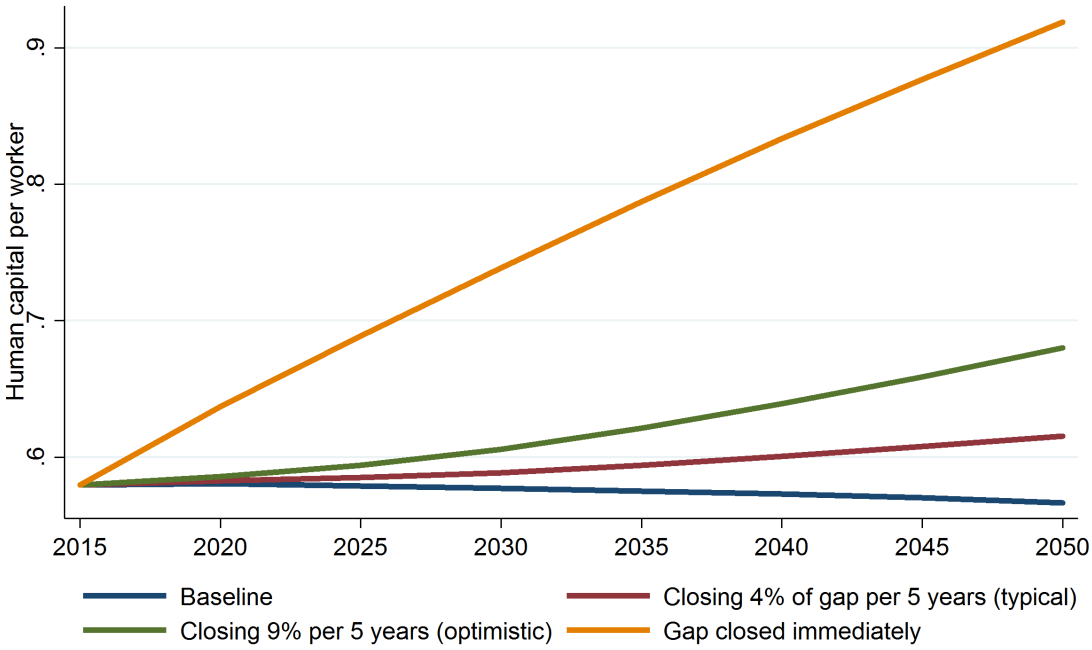


Figure 3: Projected GDP per capita for world

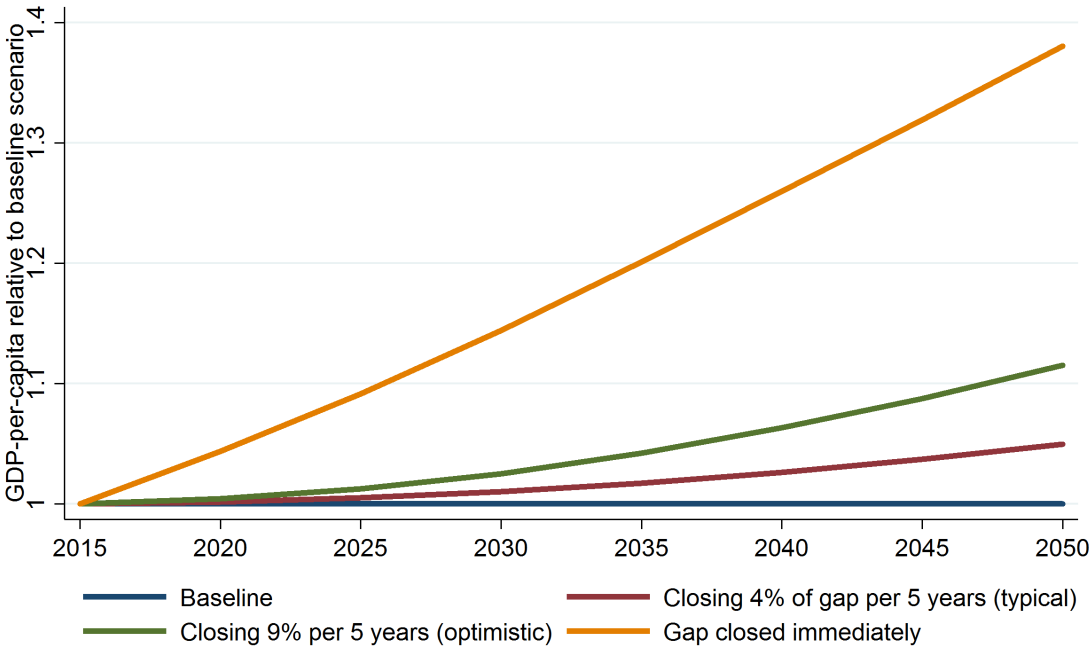
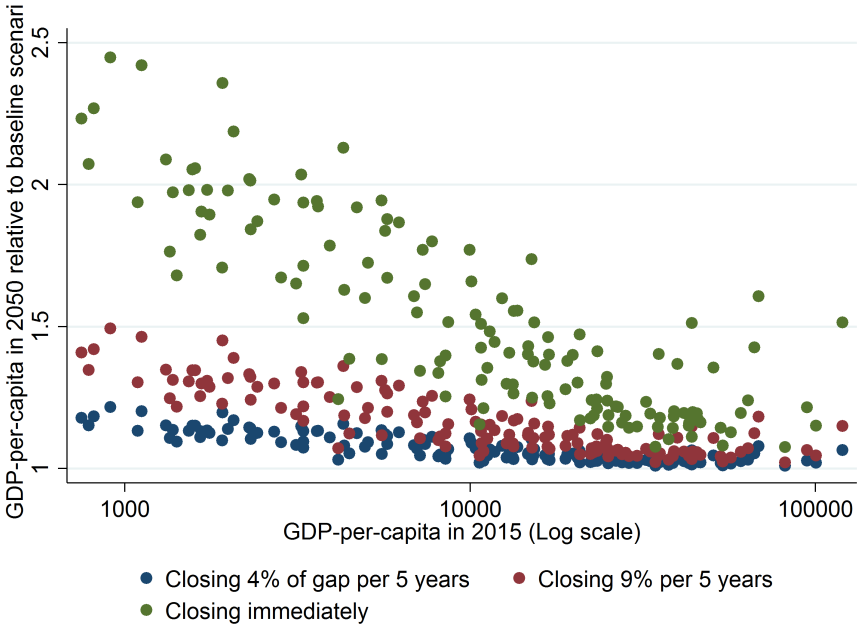


Figure 4: Correlations between income and relative income gains under each scenario



The higher relative gains for poorer countries is driven by their low levels of human capital, as an given percentage reduction in the HCI gap implies a larger increase in absolute levels of human capital investments. Additionally, the returns to those investments are higher for countries with low levels of the HCI. Figure 4 indicates the relationship between initial income and the gains from each of the three scenarios in our model.

3.3 Poverty

Figure 5 shows projections of the global poverty rate, using three different cutoffs for poverty ($1.90, $3.20, and $5.50 per day, all at PPP). As above, we show the baseline scenario as well as three alternatives.

As mentioned above, there is already a good deal of income growth, and thus poverty reduction, built into the baseline scenario. This results from productivity growth and demographic change, as well as the rise in human capital that results from younger cohorts replacing the less educated older ones. In the baseline scenario, $1.90 poverty worldwide declines from roughly 10 % in 2015 to 5.9% in 2030 and 3.2% in 2050. In the typical scenario, $1.90 poverty worldwide declines to 5.6% in 2030 and 2.5% in 2050. (As discussed above, the figure for 2030, exactly matches the World Bank forecasts for the expected decline in poverty by this time, since this was the target we used in calibrating productivity growth.) In 2050, the typical, optimistic, and immediate scenarios indicate that poverty will be 0.7, 1.4 and 2.5 percentage points lower than they would be in the baseline. The relative differences between the scenarios are noticeably greater for higher poverty lines,

Figure 5: Poverty projections

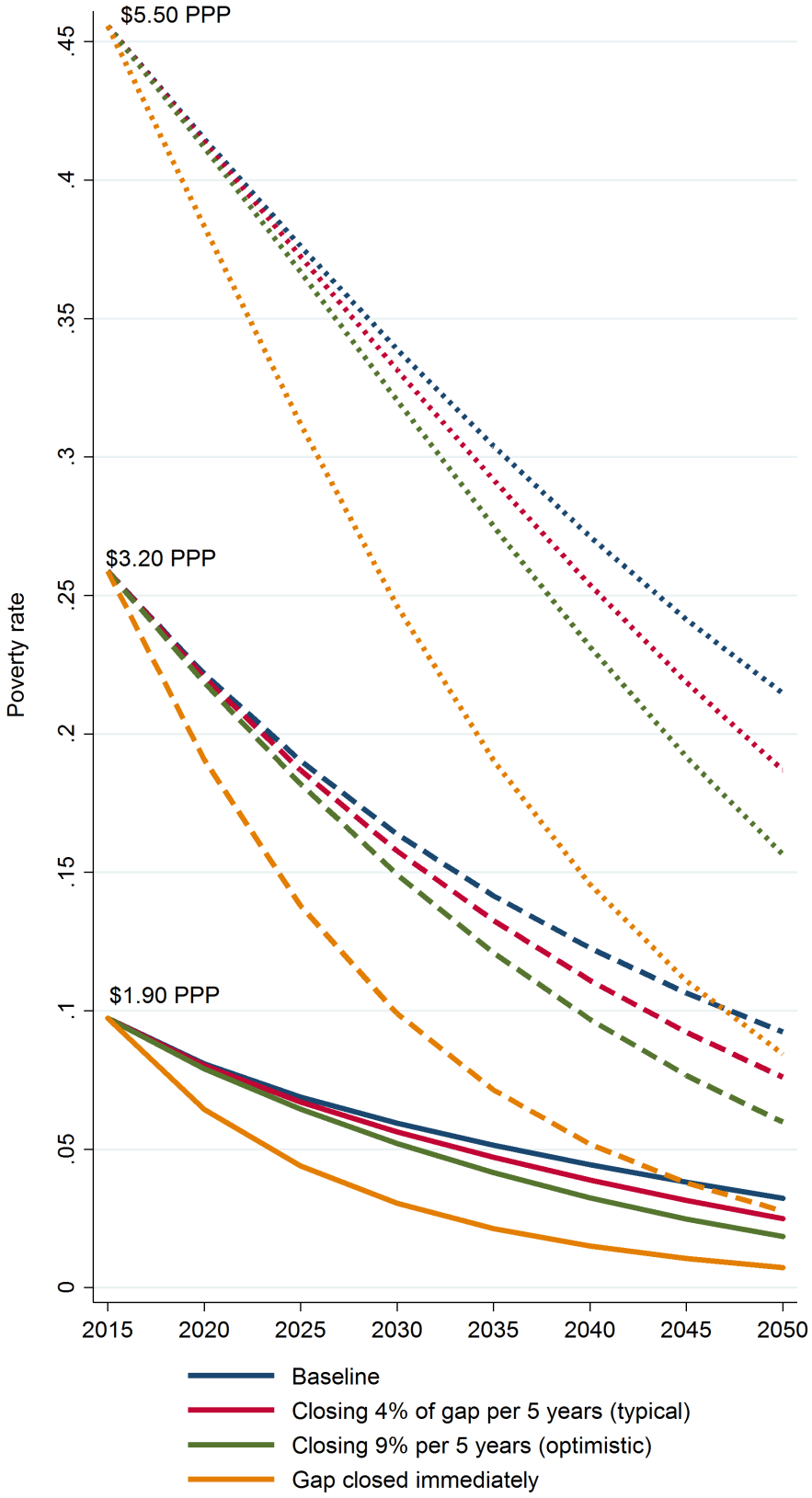
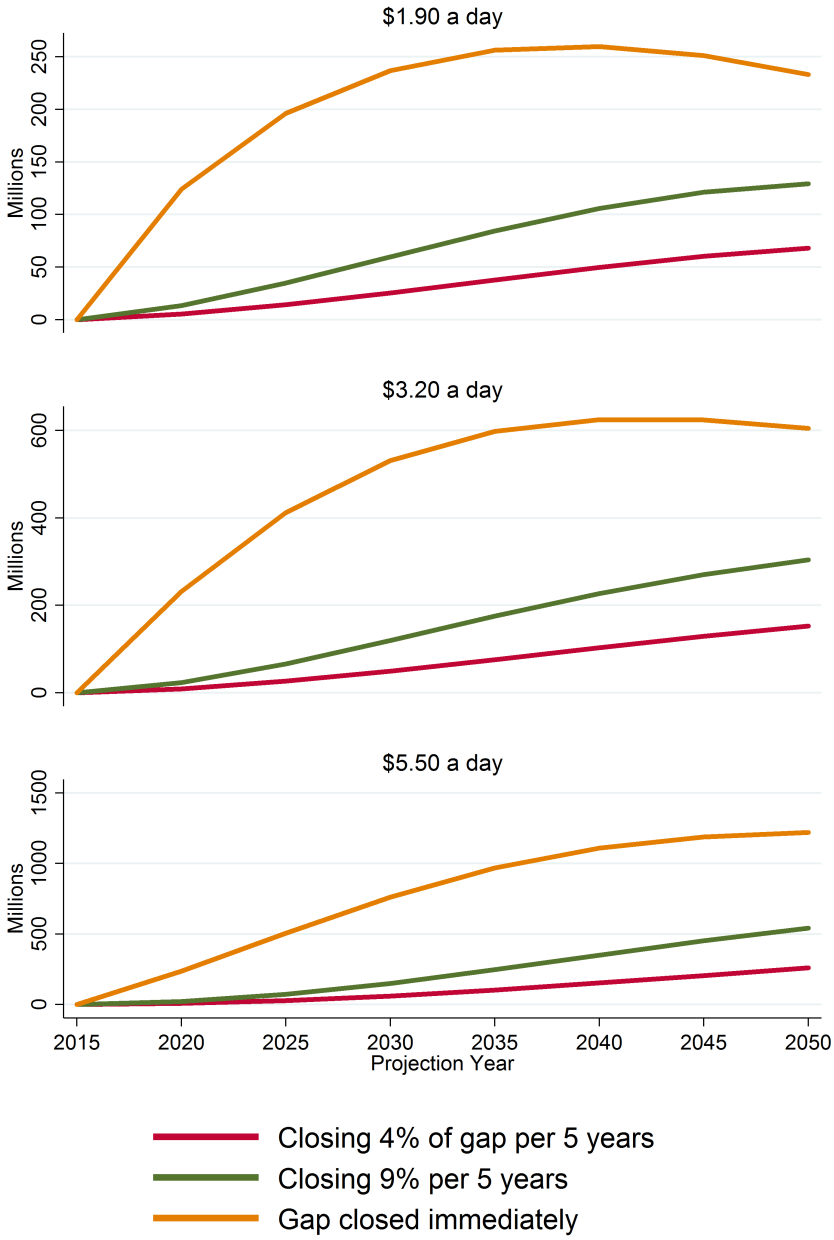


Figure 6: Number of people not in poverty, relative to baseline



in part due to the fact that absolute poverty will be nearly eliminated under any scenario, leaving less room for the growth effects of human capital investments.

In Figure 6 we consider the number of people who would have been poor in the baseline scenario, but are not in our other three scenarios. Under the optimistic scenario, roughly 130, 300 or 540 million fewer people will be in poverty by 2050 than would have otherwise been under the \$1.90, \$3.20 and \$5.50 poverty lines respectively.

4 Human Capital vs. Physical Capital Investments

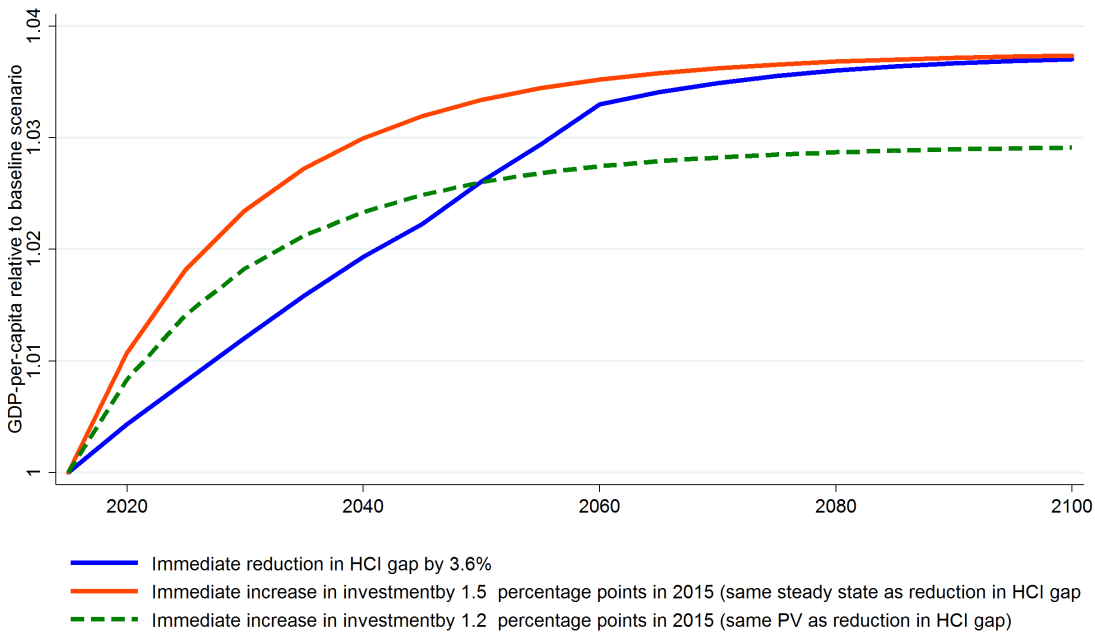
Throughout this paper we have been examining the potential for increased investment in human capital, as captured by the HCI, to raise economic growth and reduce poverty. Naturally, before endorsing such a policy it would be useful to compare its cost/benefit ratio with alternatives. The most natural of these to consider is investment in physical capital. A full comparison is beyond the scope of the current paper, because we have not in fact specified the costs of raising HCI. To cast some illumination on the issue, we proceed along a different track, which is to compare the magnitude of increases in HCI and in physical capital that would be required to achieve a specific increase in output (and reduction in poverty) in the steady state. We can also use our dynamic model to examine the time paths of output and poverty in response to these two different interventions.

To be concrete, we consider a specific country, Cambodia. In 2015, the value of human capital per worker among 20-24 year olds was 0.493. The investment rate averaged over 2006-15 was 21.1%. Consider now the effect of raising human capital investment such that the HCI gap closes by 3.6%, as occurs in the first five-year period of the typical scenario. For simplicity, we consider only this one time change, rather than looking at a full path of changes in HCI. The 3.6% decrease in the gap means that investment rate for new workers will rise from 0.488 to 0.506, an increase of 3.8%. It is easy to show that an increase in human capital investment of this magnitude would raise GDP per capita by 3.8% in steady state.

We now ask what increase in physical capital investment would be required to achieve the same steady state increase in income. In the Solow model, steady state output per capita is proportional to the investment rate raised to the power $\frac{\alpha}{1-\alpha}$. Using a value of one-third for α , this implies that raising steady state GDP per capita by a factor of 1.0377 would require the investment rate of increase by a factor of $1.0377^2 = 1.0768$. In the case of Cambodia, this would mean raising the investment rate from 20.1% to 21.7%, or 1.5 percentage points.

While the two changes in policy just considered would have the same steady state effects, the transitions to the steady state would be different. Put differently, both human capital and physical capital investments take time to fully bear fruit, but the time profiles of their effects are not the same. In particular, the human capital stock takes longer than does the physical capital stock to respond to a change in investment.

Figure 7: Dynamics of human capital vs physical capital investments in Cambodia



To flesh out this point, we consider the effects on output in our model for Cambodia of the two policies just described – raising human capita per new worker from 0.488 to 0.506 or raising the physical capital investment rate from 20.1% to 21.7%. In both cases, we assume the change takes place such that the new physical or human capital affects output starting in the year 2020.

The red and blue curves in Figure 7 show the resulting time paths for output, relative to our standard baseline in which both investment rates remain unchanged. The figure makes clear that the benefits from increased physical capital investment show up in output much more quickly than those for human capital. For example, in the year 2030, output in the case of increased physical capital investment is 2.4% above baseline, while it is only 1.2% above baseline in the case of increased human capital investment. Indeed, this analysis may even understate the delay in output gains that come from human capital investment, since we assumed that in response to the higher investment, workers fully benefiting from this increased investment began showing up in the labor force in 2020. In fact, a sudden increase in investment in children would not produce this sort of sudden increase in the quality of new workers because the first cohorts to mature under the new regime would have passed through most of their education years under the old one.

As a way of adjusting for this difference in the timing of effects from increasing human vs. physical capital, we re-run our analysis by finding the change in physical capital investment that would produce the same present value of output increases as the change in human capital investment that we already specified. We use a 4% per year time discount

rate and carry out the calculation to the year 2100.[8] In the case of Cambodia, the change in physical capital investment is 1.2 percent of GDP, and the resulting path of output is shown as the dashed green line in Figure 7.

We repeated this analysis for all of the countries in our data set, calculating the change in the investment rate that would be equivalent, in terms of the present value of GDP per capita, to a closing of the HCI gap by the typical or optimistic increments. For the set of low income countries, the average increase in investment required in the typical case is 2 percentage points; for lower middle income countries it is 1.4; for upper middle it is .9. For the optimistic case the number are 5.4, 3.8, and 2.3 percentage points.

Using these rates of human capital and physical capital investment increases that produce equally large increases in income (in a present value sense), we can take a preliminary stab at answering the question of which policy is more cost effective. Our analysis is necessarily tentative, because we don't have a full accounting of the monetary costs of raising human capital investment: we have measured this investment in units of productivity (years of quality-adjusted schooling and health of the labor force), rather than in terms of spending.

Consider again the case of Cambodia. As mentioned above, the increase investment required in our exercise is 1.2%, which is close to the average for the lower middle income country group to which Cambodia belongs. Increasing physical capital investment by this much costs 1.2% of GDP. We do not think that raising human capital investment by the amount specified would cost even half this much. In Cambodia, total health expenditure is 6% of GDP, while public expenditure for education is 2%. Even allowing for unmeasured opportunity cost and private educational expenditures, it seems likely that total expenditures for producing human capital are currently less than 10% of GDP. If there were constant returns, a 4.9% increase in human capital investment, which is what we specified in our experiment, would require an increase in expenditure of only 0.49% of GDP.

5 Conclusion

Gaps among countries in the rate at which they invest in the human capital of their citizens are large. Taking a broad measure that includes quality and quantity of education as well as measures of the effect of health on worker productivity, there is a gap ranging as high as a factor of three between the human capital of new workers in high investing countries relative to those that invest the least. Investment rates in human capital are highly correlated with income per capita, and indeed, the lower labor input of workers,

[8] We choose the discount rate following the logic of Ramsey discounting, under which increases in consumption are worth less when they come on top of a higher base. Under log utility, the proper discount rate is simply the sum of the pure social discount rate, which we assume to be 2%, and the rate of consumption growth. The value of productivity growth that we use implies steady state consumption growth of 1.95% per year.

due to their health and education deficiencies, is an important contributor to the poverty of many countries.

These observations suggest that raising investment in human capital represents an attractive policy for increasing income and reducing poverty. In this paper we have quantitatively explored the dynamic responses of income and poverty to such increased investment. Consideration of the time dimension is particularly important in this case because the benefits of higher human capital investment have very long gestation periods: it takes a long time to produce a new worker, and an even longer time before existing workers, who were subject to lower human capital investments during their youth, cycle out of the labor force.

Our main exercise compared the paths of income and poverty that would be experienced under two specified scenarios to those experienced on a baseline in which the rate of human capital investment currently observed in every country remains constant into the future. In one scenario (labelled "typical"), each country experiences a rate of growth of human capital investment that is typical of what was observed in the decade ending in 2015. In this scenario, world GDP per capita is 5% higher than baseline in the year 2050, while the global rate of $1.90 poverty is 0.7 percentage points lower in that same year. In the "optimistic" scenario, in which each country is assumed to raise the components of human capital investment at a rate corresponding to the 75% of what was observed in the data, world GDP per capita is 12% higher than baseline in 2050, while the rate of $1.90 drops by 1.4 percentage points. Under the optimistic scenario, roughly 130, 300 or 540 million fewer people will be in poverty by 2050 than would have otherwise been under the $1.90, $3.20 and $5.50 poverty lines respectively.

The increase in incomes and declines in poverty that would be observed in developing countries are significantly larger than the world averages, because these countries are faced with much larger gaps between their current investment rates and the level that would represent full investment in the next generation. For example, among low income countries (using the World Bank classification), GDP per capita would be 12% higher in the typical scenario and nearly 25% higher in the optimistic scenario in the year 2050 than in the baseline.

We also used our model to compare the dynamics of output growth in response to higher human capital investment to those resulting from higher investment in physical capital. The latter delivers its growth benefits much more quickly – that is, a country can build more machines and infrastructure at a faster pace than it can build better workers. That being said, our informal comparison of the costs of the two types of investments suggests that investing in people is sufficiently cheap in comparison to investing in machines to overcome the timing advantage associated with investing in machines.

Although our analysis includes some of the channels by which higher human capital would raise income, for example, by inducing the accumulation of more physical capital, we also leave out some potentially important mechanisms. First, a natural expectation

would be that raising quality and quantity of education, particularly of women, would reduce fertility both by raising the opportunity cost of children and increasing women's control over their own childbearing. Lower fertility would in turn impact future dependency ratios in a manner that further increased income per capita and lowered poverty (Canning and Raja 2015). A second channel leads through higher human capital to higher productivity growth, through education's effect on innovation, management quality, and adaptation to changing economic circumstances.

There is also likely a downward bias in the size of the poverty reductions that we forecast in response to rising human capital investment. Our simulations assume that income inequality would not be affected by higher investment in children. In practice, it is poorer children in whom investment is most deficient, and thus this is the group most likely to benefit from an increase. If higher human capital investment meant more equal human capital investment, then the decline in poverty would be larger than what we forecast.

Finally, although we have stressed the instrumental value of investing in human capital in terms of producing income (both for the country as a whole and for poor people), it is worth remembering that the kinds of investments that we are evaluating pay dividends in other dimensions as well. The education that results from more years and/or higher quality schooling allows individuals to lead more fully actualized lives and to participate more actively in their societies. And better health, which we have considered solely in terms of making workers more productive, also allows people to enjoy more years of life. Taking these benefits into account would further strengthen the case for raising human capital investment.

References

Altinok, N., N. Angrist, and H. A. Patrinos (2018). Global data set on education quality (1965–2015).

Angrist, N., D. Filmer, R. Gatti, H. Rogers, and S. Sabarwal (2018). Learning-adjusted years of schooling (lays): Defining a new macro measure of education. Technical report, World Bank Policy Research Working Paper, no. WPS8592.

Ashraf, Q. H., A. Lester, and D. N. Weil (2008). When does improving health raise gdp? *NBER macroeconomics annual 23*(1), 157–204.

Barro, R. J. and J. W. Lee (2013). A new data set of educational attainment in the world, 1950–2010. *Journal of development economics 104*, 184–198.

Canning, D. and S. Raja (2015). Economic effects of the demographic dividend. In S. R. David Canning and A. S. Yazbeck (Eds.), *Africa's Demographic Transition: Dividend or Disaster?*, pp. 129–168. World Bank.

Caselli, F. (2005). Accounting for cross-country income differences. *Handbook of economic growth 1*, 679–741.

Caselli, F. (2016). The latin american efficiency gap. In W. Araujo, Vostroknutova and Clavijo (Eds.), *Understanding the Income and Efficiency Gap in Latin America and the Caribbean*. World Bank.

IHME (2015). Global educational attainment 1970-2015. Technical report, Institute for Health Metrics and Evaluation.

Kraay, A. (2018). Methodology for a world bank human capital index. Technical report, World Bank Policy Research Working Paper, no. WPS8593.

Schoellman, T. (2011). Education quality and development accounting. *The Review of Economic Studies 79*(1), 388–417.

United Nations Department of Economic and Social Affairs, Population Division (2017). World population prospects: The 2017 revision, volume i: Comprehensive tables. Technical report, UN.

Weil, D. N. (2007). Accounting for the effect of health on economic growth. *The quarterly journal of economics 122*(3), 1265–1306.

A Data Appendix

A.1 Converting IHME data on educational attainment to Barro-Lee

As described above, data from the latest edition of Barro-Lee provides years of schooling data for 143 countries. Supplementing it with data from IHME (2016) allows us to expand our coverage (of years of schooling) from 143 to 190 countries.

However, where Barro-Lee provides year of schooling broken down by primary, secondary and tertiary education, IHME's public data only provides a measure which combines all three with pre-primary education.

We rely on the following method to convert IHME's combined measure to one which just comprises primary and secondary education. First we establish an empirical relationship between $EA_{a,n}^{IHME}$ and $EA_{a,n}^{BL,P+S+T}$, where the latter is years of schooling in Barro-Lee, including tertiary. We do this for the last year we have data for both (2010) for all working-age cohorts. To be precise, we run a quadratic regression of the following form:

$$EA_{a,n}^{BL,P+S+T} = \alpha + \beta_1 EA_{a,n}^{IHME} + \beta_2 (EA_{a,n}^{IHME})^2 + \varepsilon_{a,n} \tag{27}$$

And recover values for α β_1 and β_2. We use these values to convert IHME years of schooling to Barro-Lee years of schooling. We then need to convert these units (which are primary + secondary + tertiary) into their primary + secondary equivalents. To do so, we run a regression of the following form, using all available Barro-Lee data for working-age cohorts from 2010:

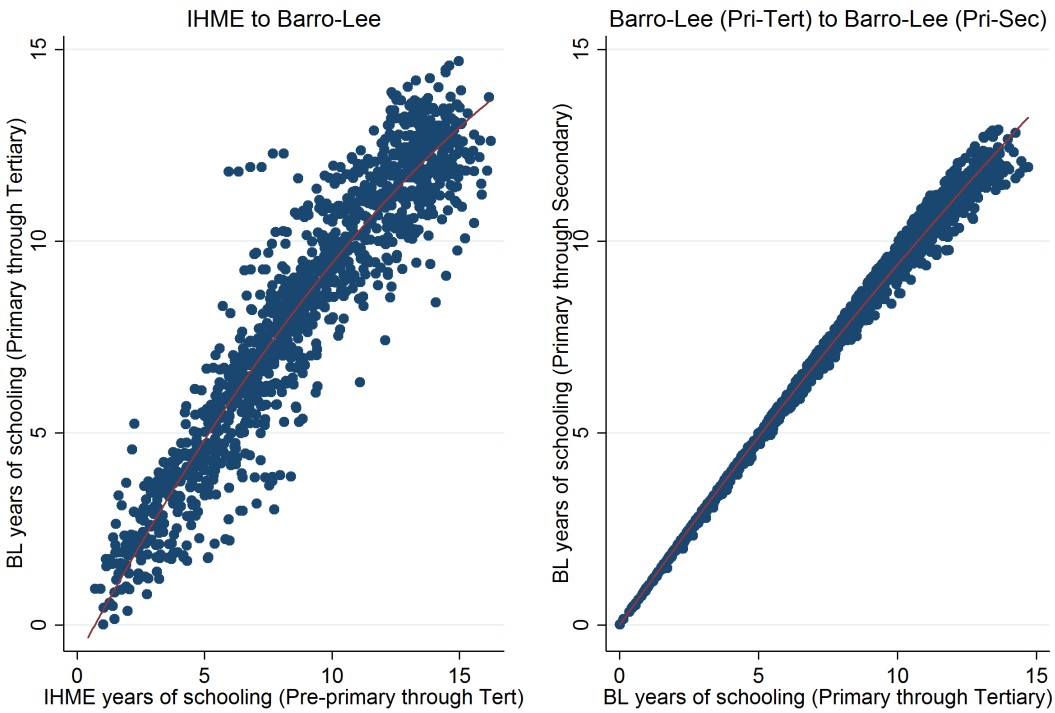
$$EA_{a,n}^{BL,P+S} = \lambda_1 EA_{a,n}^{BL,P+S+T} + \lambda_2 (EA_{a,n}^{P+S+T})^2 + \varepsilon_{a,n} \tag{28}$$

And use the values of λ_1 and λ_2 to adjust the above values. In summary, we calculate predicted Barro-Lee primary + secondary years of schooling by calculating:

$$\widehat{EA}_{a,n}^{BL,P+S} = \lambda_1 \Big(\alpha + \beta_1 EA_{a,n}^{IHME} + \beta_2 (EA_{a,n}^{IHME})^2\Big) + \lambda 2 \Big(\alpha + \beta_1 EA_{a,n}^{IHME} + \beta_2 (EA_{a,n}^{IHME})^2\Big)^2 \tag{29}$$

We then convert these 2010 estimated Barro-Lee years into 2015 years using the methods described in Section 2.2.

Figure 8: Converting IHME years of schooling (Primary-Tertiary) to Barro-Lee (Primary-Secondary)



Note: red line indicates predicted values from quadratic regression