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

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Keywords: Human Capital, Economic Growth

JEL classification: I10,I20,O4

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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 than 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.

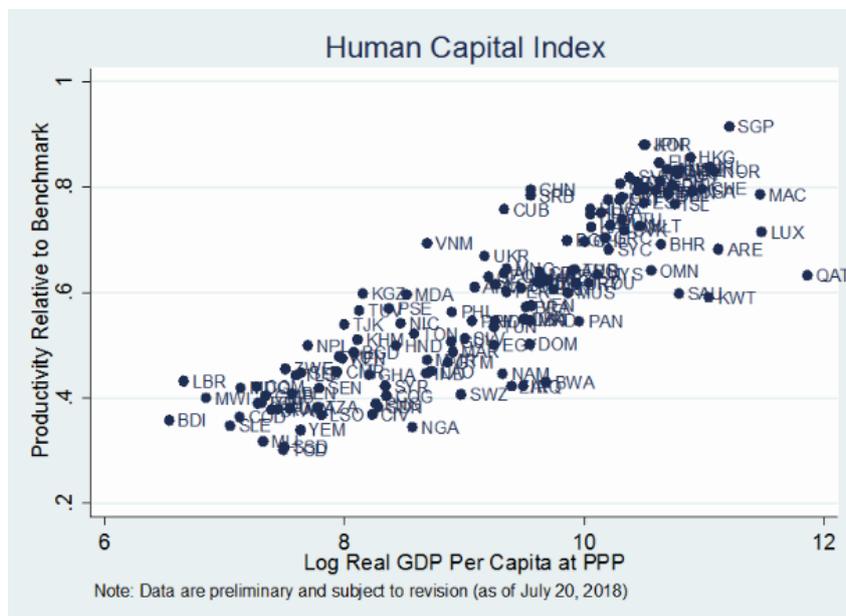
A recent World Bank project (see [Kraay \(2019\)](#)) has produced the Human Capital Index (HCI), a new measure of the flow rate of human capital investment across countries. The HCI incorporates data on school attendance rates, test scores, and health (combining adult health, as measured by survival 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, Cuba, and Vietnam all have unexpectedly high HCI given their levels of income, while a number of oil producers have unexpectedly low levels.

The high correlation of the HCI and income reflects causality flowing in both directions: richer countries can afford to invest more in their children, but also higher rates of investment eventually lead to higher levels of human capital which contributes to the production of output. 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

¹Related 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

Figure 1: The human capital index



Source: Kraay (2019)

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 (2019), 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 investment² 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 the workforce. In addition, there is an follow-on effect from higher human capital investment, via the accumulation of physical

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 than using test scores as in Kraay (2019) 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.

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

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 \(2008\)](#).

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 from [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 how the amount of physical capital evolves over time, under the assumption that the investment rate stays fixed at its 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 adults 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 (that is, different assumptions as to how the human capital of the youngest generation of workers evolves over time). 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 re-

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

ceived 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 countries, this “demographic dividend” will be of significant magnitude. Third, we expect productivity to grow going into the future, as it has historically.⁴ 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. 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

⁴A potentially important omission in our model is any linkage between human capital accumulation and productivity growth. In many endogenous growth models, human capital is the engine of growth, either because it endogenously grows itself (Lucas Jr 1988; Ehrlich and Kim 2007), because it speeds up the creation of new technologies (Ehrlich 2007), or because it facilitates the import of cutting-edge technology from abroad (Jones 2003). To the extent that any of these channels are operative, increased human capital accumulation will have a larger effect on growth than what we model. In the developing countries that are our central concern in this paper, the third channel is probably the most relevant. Unfortunately, we do not have good structural estimates of the role of human capital in facilitating technology transfer that we can apply.

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 do not include in the basic model of Sections 2-4 is the effect of parental human capital on fertility and on children's human capital investments. In Section 5, we address this deficiency, integrating the results from our simulation with existing estimates of the effect of education on fertility and of fertility on income, the latter running through several different channels. We find that allowing for this additional causal channel greatly amplifies the estimated impact of an initial increase in human capital investment in raising income.

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 the level of inequality in a country (the Gini coefficient) would be the same in the alternative scenarios 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.

The rest of this paper is organized as follows. Section 2 lays out our model, discusses the underlying data, and describes the different scenarios we analyze. Section 3 presents the simulated paths of income per capita and poverty in the different scenarios. In Section 4, we consider the relative efficacy of human capital investment and physical capital investment for achieving a given increment to income growth. Section 5 discusses an extension of the model to take into account the effect of higher human capital investment on fertility, and of fertility on income and human capital investment. Section 6 concludes. Appendix A.2 compares our findings to an alternative version of the model that includes tertiary education, while Appendix A.1 describes comparability issues in mapping between the Institute for Health Metrics and Evaluation (IHME) and Barro-Lee datasets.

2 Model Specification

In this section we describe in more detail the model we use to simulate the effects of changes in human capital investment 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 inputs. 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 \(2019\)](#) 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's medium variant estimates ([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. Our primary reason for ignoring tertiary education is that available data on school quality (discussed below) are only applicable to primary and secondary education. We were not comfortable assuming that the measured differences apply to tertiary education. In Appendix A.1, we extend the model to include tertiary education, and show that in fact the predictions regarding the paths of income and poverty are very similar to those in our main exercise.

In this paper, we assume that the level of human capital observed in 20-24 year olds in 2015 corresponds to Human Capital Index: it measures the flow of human capital investment. For example, if the HCI takes on a value of 0.75 for a country in 2015, we assume this means that 20-24 year olds in that year will have a level of human capital of 0.75 (even though the level of human capital for the rest of the workforce may be different).

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

$$WrkAge_t = \sum_{a=20}^{60} P_{a,t} \quad (1)$$

And the fraction of the Working Age Population as

$$WrkAgeFract_t = \frac{WrkAge_t}{\sum_a P_{a,t}} \quad (2)$$

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

$$GDPperWorker_0 = \frac{GDP_0}{WrkAge_0} \quad (3)$$

And GDP per capita as

$$GDPperCapita_0 = GDPperWorker_0 \times WrkAgeFract_0 \quad (4)$$

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:

$$KperWorker_0 = \frac{K_0}{WrkAge_0} \quad (5)$$

Education Attainment

We obtain data on educational attainment each five year age group from two sources. The first is Barro-Lee's 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).⁵

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. 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 A.2. 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 12.⁶

Education Quality

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

⁵It is worth noting that the World Bank’s version of the HCI uses expected years of schooling (EYS) as produced by UNESCO. We deviate from the WB methodology in this case as EYS is not broken own by age groups, which is necessary for our simulation exercise.

⁶Note 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.

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

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

$$AdjEd_{a,0} = EA_{a,0} \times EQ_0 \quad (8)$$

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

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

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

$$HCHhealth_{a,0} = e^{\frac{(\gamma_{ASR} \times (ASR_0 - 1) - \gamma_{Stunting} \times Stunting_0)}{2}} \quad (10)$$

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

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

We use values of $\gamma_{ASR} = 0.6528$ and $\gamma_{Stunting} = 0.3468$ based on [Weil \(2007\)](#) and [Kraay \(2019\)](#).

Total Human Capital

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

$$HC_{a,0} = HCSchool_{a,0} \times HCHealth_{a,0} \quad (12)$$

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:

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

Productivity at $t = 0$

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

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

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

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

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.

$$\sigma = \Phi^{-1}\left(\frac{Gini_0 + 1}{2}\right) \times \sqrt{2} \quad (16)$$

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

$$Pov_0 = \Phi\left(\frac{\ln(P) - \mu_0}{\sigma}\right) \quad (17)$$

Rearranging,

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

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.

$$\frac{m_t}{m_0} = \frac{GDPperCapita_t}{GDPperCapita_0} \quad (19)$$

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

$$\mu_t = \mu_0 + \ln\left(\frac{GDPPerCapita_t}{GDPPerCapita_0}\right) \quad (20)$$

The expression for the poverty headcount at time t is:

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

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

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

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:

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

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.

$$\begin{aligned} HC_{20,t+1} &= HC_{20,0} \\ HC_{a+5,t+1} &= HC_{a,t} \quad \text{for } a = 25 \dots 60 \\ HC_{perWorker}_t &= \frac{(\sum_{a=20}^{60} P_{a,t} \times HC_{a,t})}{WrkAge_t} \end{aligned} \quad (23)$$

Capital evolves as follows:

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

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

$$GDPperWorker_t = A_t \times KperWorker_t^\alpha \times HCperWorker_t^{1-\alpha} \quad (25)$$

$$GDPperCapita_t = GDPperWorker_t \times WrkAgeFrac_t \quad (26)$$

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 out of the workforce. We next consider three alternative scenarios where the entire HCI, the human capital of workers age 20-24, 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 World Bank's 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 as measured in the latest version of the HCI in 2017. That is, what the change in the HCI would be if a country with EYS of 11.78, harmonized learning outcomes of 423.57, non-stunted rates of 0.77, and adult survival rates of 0.87 increased these outcomes by 0.474, 6, 0.051 and 0.022 respectively.

Specifically, we consider the percentage change in the "HCI gap," the difference between 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.

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

Outcome	Change between 2005-2015		Median value in 2017
	50th percentile	75th percentile	
Expected years of schooling	0.474	1.131	11.78
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

If a country with median values of the components 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% (.0072) of the HCI gap every year, or roughly 4% (.0353) every five years.

To simulate this scenario, rather than simulate changes in all the components of human capital, we will instead apply a 4% (.0353) 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 that⁷

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

The implication of applying a uniform percentage decrease in the HCI gap is that countries with lower levels of the HCI will face higher levels of subsequent growth. For example, low income countries, on average, have starting levels of human capital $HC_{20,2015} = 0.43$, but see an increase by 0.0201 in the first five years. By contrast, upper middle countries have on average $HC_{20,2015} = 0.63$, but only see an increase of 0.013 in the first five years.

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% (.019) annual decrease in the HCI gap, equivalent to approximately a 9% (.0914) 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.

⁷Note 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.

Table 2 provides a summary of each of the four scenarios.

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.”⁸

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 0.57 to 0.56, driven primarily by demographic trends.⁹ Under the typical and the optimistic scenarios, human capital per worker rises modestly, from approximately 0.57 to 0.61 and 0.67, 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 39% higher

⁸Throughout the time period we consider in this paper, our results cover roughly 90-92% of the world population.

⁹This is driven by the fact that, by 2050, countries with lower levels of human capital are projected to have higher global population shares relative to countries with higher levels of human capital. To illustrate this, we re-calculate human capital per worker in the baseline scenario, but holding each country’s population fixed at its 2015 levels. When we do this, global human capital per worker increases over the course of the simulation, from 0.57 in 2015 to 0.59 in 2050.

Table 2: Summary of each scenario

	<i>Baseline</i>	<i>Typical</i>	<i>Optimistic</i>	<i>Immediate</i>
Description	Human capital investments stop improving	Countries improve at same rate as median historically	Countries improve at same rate as 75th percentile	Human capital investments max out
Evolution of HCI	Remains fixed at 2015 values	Gap closes at 4% per period	Gap closes at 9% per period	Gap closes immediately
Human capital of 20-24 year olds ($HC_{20,t}$)	$HC_{20,2015}$	$1 - .0353 \times (1 - HC_{20,t-1})$	$1 - .0914 \times (1 - HC_{20,t-1})$	1 for $t > 2015$

Figure 2: Human capital per worker

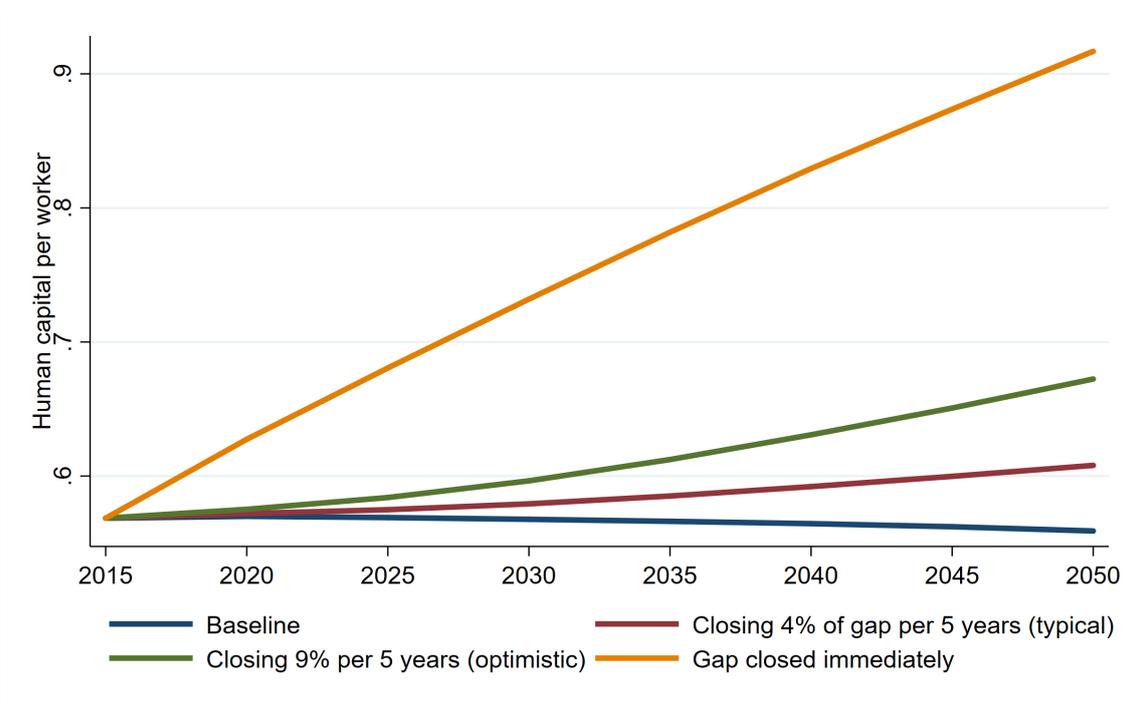


Figure 3: Projected GDP per capita for world

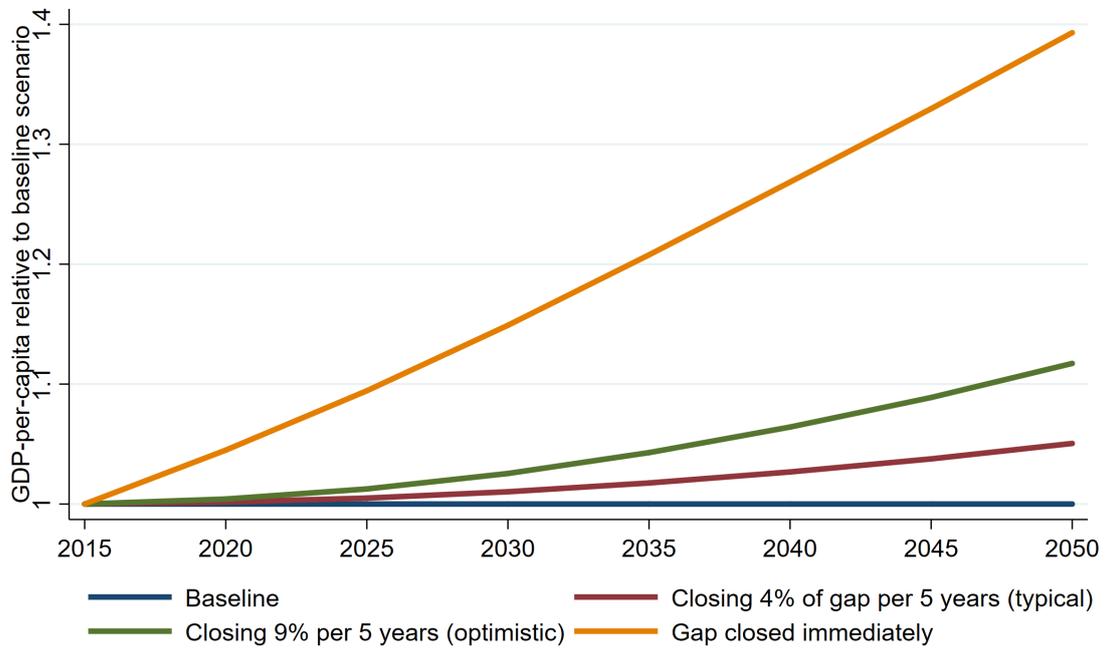
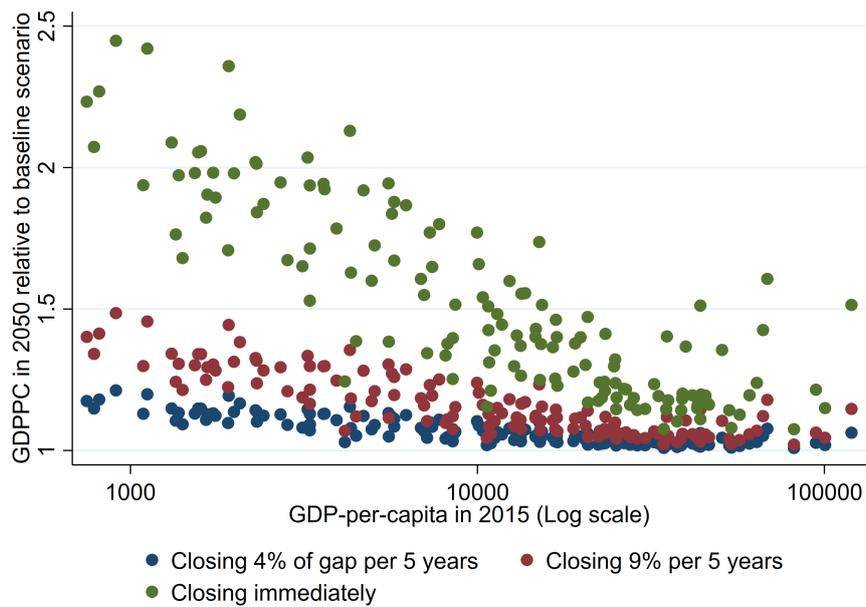


Figure 4: Correlations between income and relative income gains under each scenario



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 14% 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. The higher relative gains for poorer countries are driven by their low levels of human capital, as a 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, 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.

To break down changes in poverty rates by country, Figure 6 shows the projected rate of poverty under each scenario for all countries with a \$1.90 poverty rate higher than 10% in 2015. A number of interesting observations emerge. First, in every country, the largest reduction in poverty from its current level comes in moving to the baseline scenario, rather than in moving from the baseline to either the typical or optimistic scenario. In other words, the current level of human capital investment will, by itself, lead to a large degree of poverty reduction simply because current investment is so much higher than what was received by older cohorts of workers. Second, there are interesting heterogeneities in the way in which forecast poverty reduction compares to its current level. For example, Malawi currently has a lower poverty rate than Madagascar, but it is forecast to have

Figure 5: Poverty projections

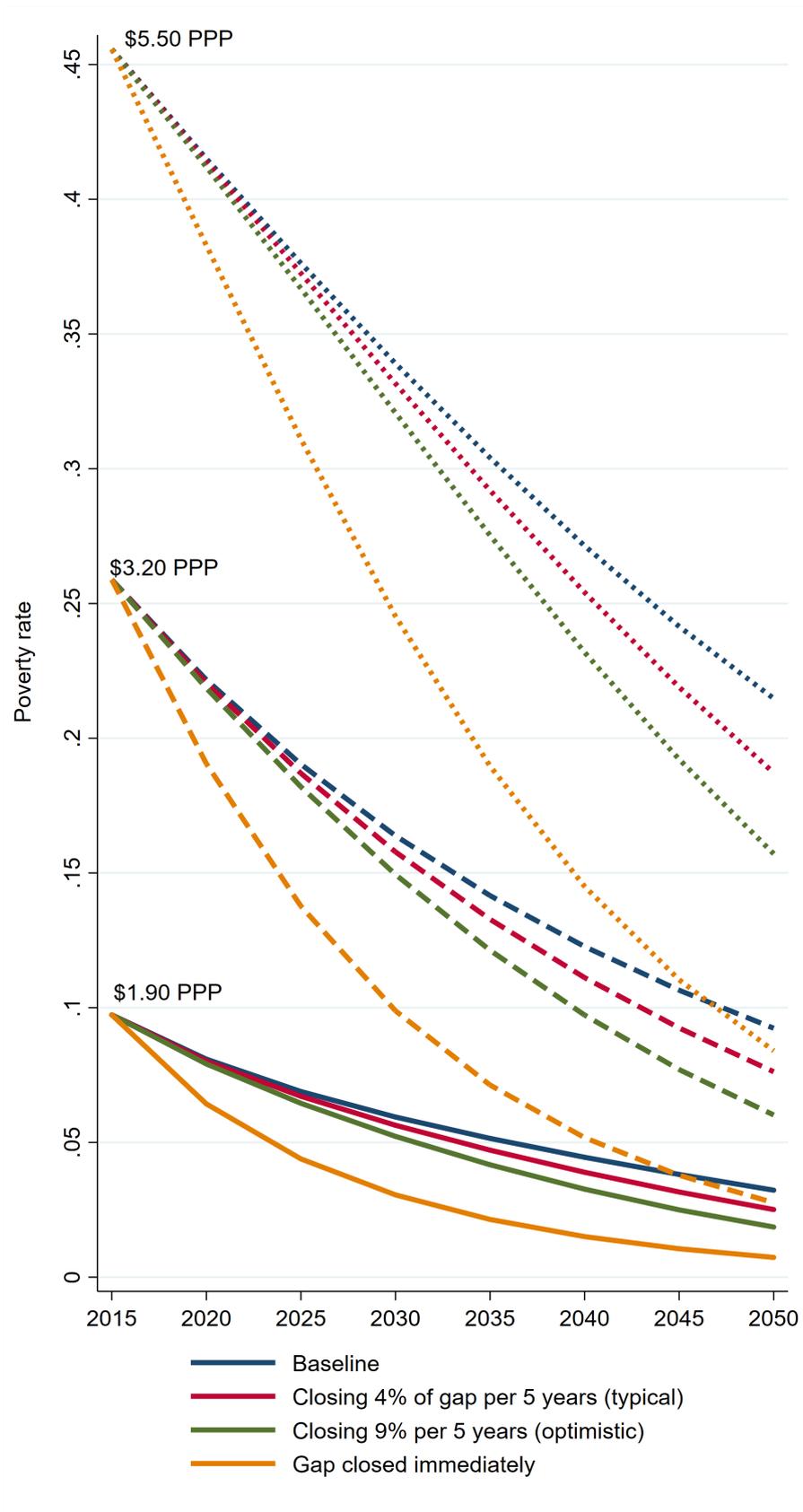
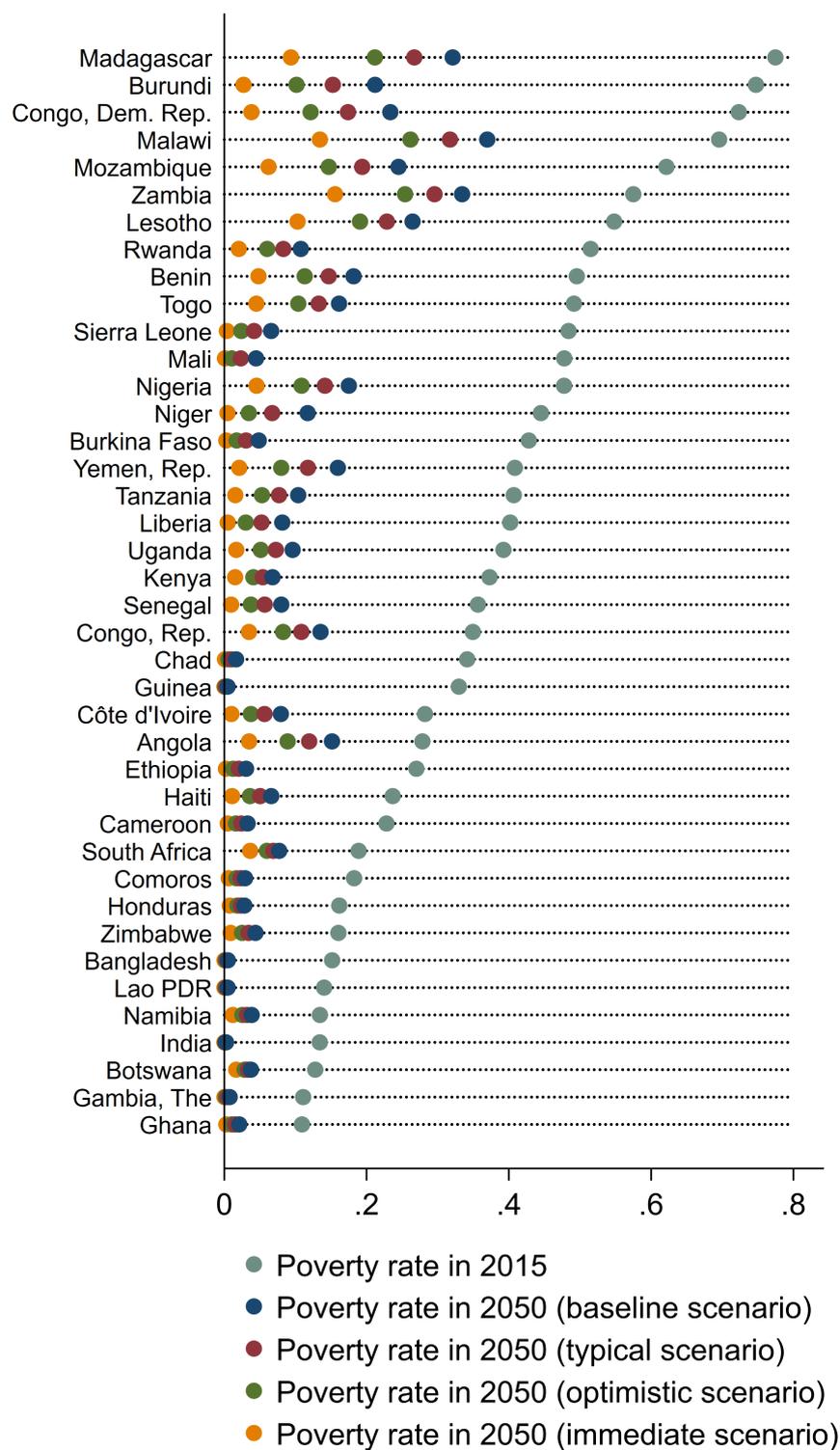
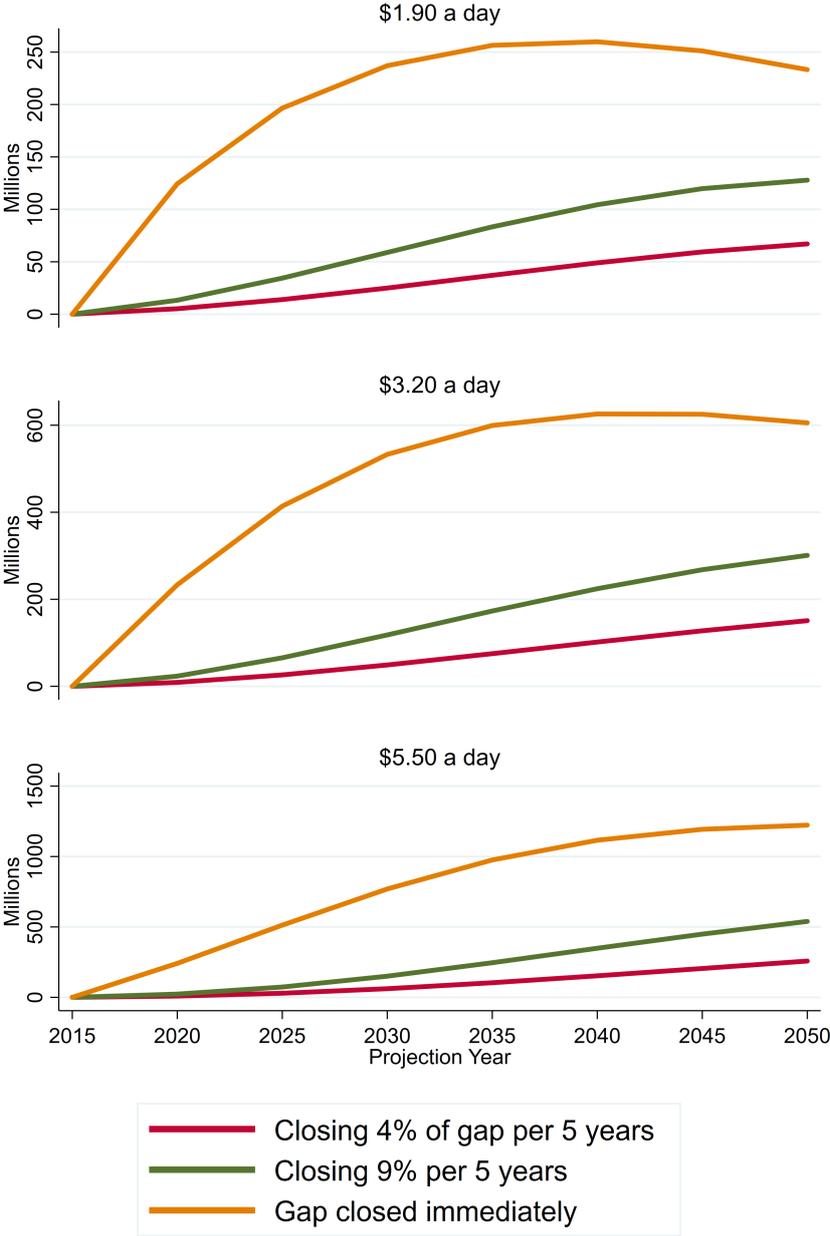


Figure 6: Changes in poverty, by country



Note: Graph shows results for \$1.90 PPP poverty for countries with poverty rates in 2015 less than or equal to 10%.

Figure 7: Number of people not in poverty, relative to baseline



higher poverty than that country in 2050 in each of the scenarios that we consider.¹⁰

In Figure 7 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.

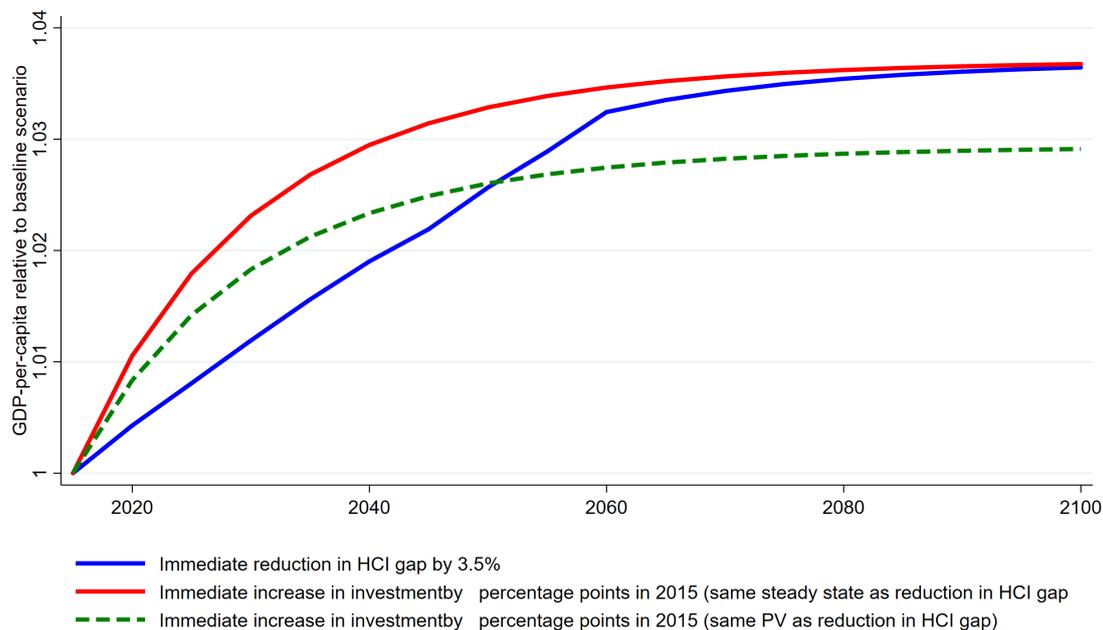
To be concrete, we consider a specific country, Cambodia. In 2015, the value of human capital per worker among 20-24 year olds was 0.488. The physical capital investment rate averaged over 2006-15 was 20.1%. Consider now the effect of raising human capital investment such that the HCI gap closes by 3.5%, 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 3.5% decrease in the gap means that investment rate for new workers will rise from 0.488 to 0.506, an increase of 3.7%. It is easy to show that an increase in human capital investment of this magnitude would raise GDP per capita by 3.7% 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 1.0371 would require the investment rate of increase by a factor of $1.0371^2 = 1.0755$. In the case of Cambodia, this would mean raising the investment rate from 20.1% to 21.6%, 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

¹⁰It is worth remembering that these projections come from a simplified model that we are using to analyze a set of stylized scenarios. They are not necessarily comparable with long-run poverty forecasts produced by the World Bank.

Figure 8: Dynamics of human capital vs physical capital investments in Cambodia



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.

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 21.6%. 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 8 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 2.3% 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 2100.¹¹ 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 8.

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 2.0 percentage points; for lower middle income countries it is 1.4; for upper middle it is 0.9. For the “optimistic” case the numbers are 5.3, 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.

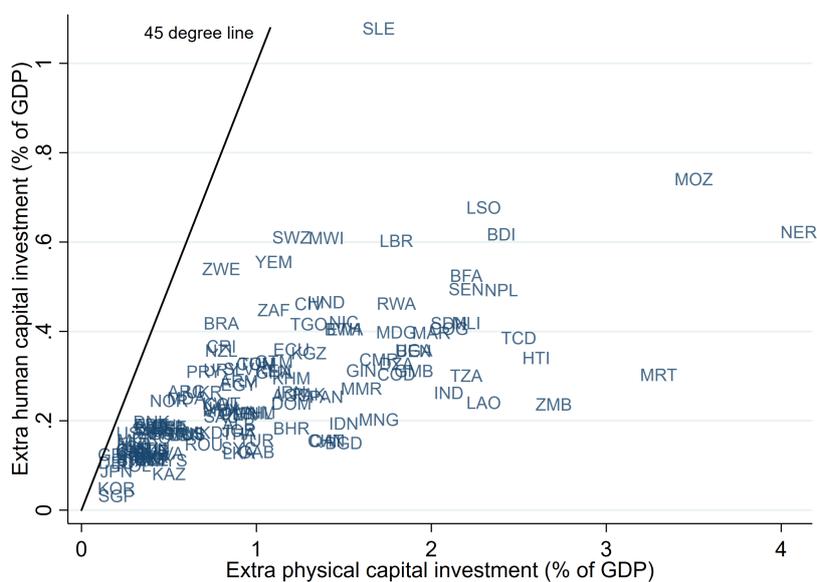
Consider again the case of Cambodia. As mentioned above, the increase in physical capital investment required in our exercise is 1.2%, which is close to the average for the lower middle income country group to which Cambodia belongs. Increasing physical capital investment by this much costs 1.2% of GDP. 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 3.7% increase in human capital investment, which is what we specified in our experiment, would require an increase in expenditure of only 0.37% of GDP.

We now extend the exercise just described for Cambodia to our full sample of countries. Specifically, for each country, we calculate the changes in physical capital investment and human capital investment that would be required to achieve equal increases in the present discounted value of output. In the case of human capital investment, we assume constant returns to scale, and take as our measure of current investment the sum of total health expenditures and public spending on education. We thus miss out on private educational expenditures as well as the opportunity cost of education, but given the lopsided result

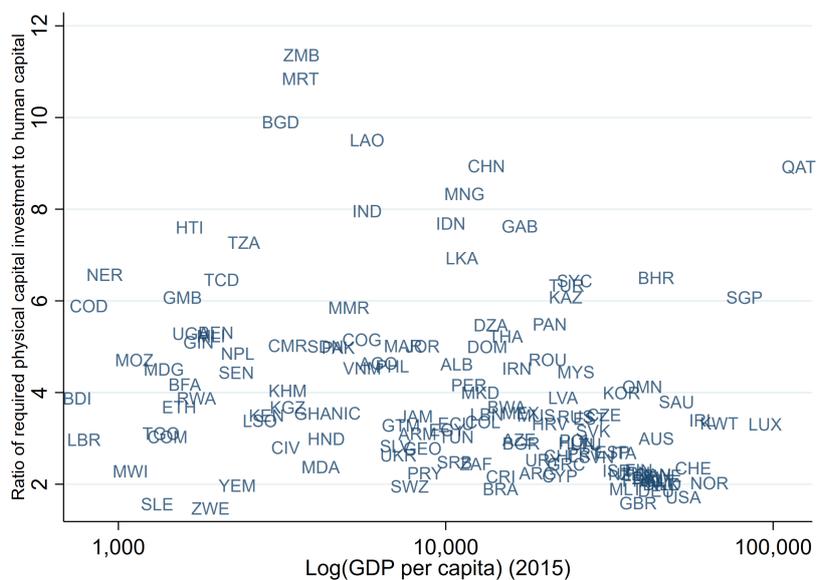
¹¹We choose the discount rate following the logic of Ramsey discounting, under which increases in consumption are worth less when they come on top of a higher base. Under log utility, the proper discount rate is simply the sum of the pure social discount rate, which we assume to be 2%, and the rate of consumption growth. The value of productivity growth that we use implies steady state consumption growth of 1.95% per year.

Figure 9: The relative cost of investments in physical and human capital

(a) Correlation between additional human capital investment necessary to close HCI gap by 3.5% in first five years and additional physical capital investment needed to match the same present value of GDP per capita



(b) Ratio of additional human capital investment to additional physical capital investment and starting levels of GDP



we find, taking these into account would be unlikely to change our findings. Figure 9a shows a scatter plot comparing the two required increases in investment. Poorer countries

in general have higher required investment increases in either physical or human capital in order to reach the target that we have specified. This is because the target involves closing a fixed proportion of the gap in human capital relative to full investment, and this gap is bigger in poorer countries. But it is notable that all of the data points in the figure lie to the right of the 45-degree line, which is to say that in all countries the required increase in physical capital investment is larger than the required increase in human capital investment. Figure 9b shows the ratio of required investment in physical capital to required investment in human capital on the vertical axis, and current GDP per capita on the horizontal. There is a slight tendency for this ratio to be higher in richer countries, but the more striking fact in the picture is that the ratio is high in all the countries in the sample, generally ranging between two and six

5 Additional Causal Channels and General Equilibrium Effects

In the paper thus far we have considered the effect of an increase in human capital investment on income and poverty by focusing solely on the productive effects of that human capital, that is, the extra output that will be produced by higher quality workers. Implicitly, we ignore other potentially important channels by which human capital might impact income and poverty, such as via an effect on fertility. We similarly ignore general equilibrium effects, for example how higher income produced by an increase in human capital will affect both fertility and future human capital accumulation, and similarly how lower fertility will affect human capital accumulation. Our proceeding in this fashion is determined primarily by the limitations on available estimates of the underlying causal relationships among these endogenous variables. In the case of human capital's effect on productivity, we were able to take advantage of existing estimates of structural parameters. But these are largely absent for other causal channels.

In some cases, we can speculate with reasonable confidence about the direction in which consideration of general equilibrium effects would alter our findings. For example, it is very likely that higher income would raise investment in human capital.¹² Thus an initial increase in the human capital investment, which our exercise shows would raise income, would in turn feed back to even more human capital investment. In other words, our exercise would understate the full effect of an initial policy-driven rise in HCI. In other cases – for example, the structural effect of income on fertility – the sign of the effect is not clear a priori.

In this section, we pursue one additional channel where we are able to get well identified structural estimates, and which seems likely to be among the more important channels

¹²One channel would be by loosening the budget constraint for households and governments. Additionally, we would expect capital accumulation from higher income to raise the return to educational investments.

omitted in our analysis. This is the effect of increased human capital on fertility and the follow-on effects of fertility on both income per capita and human capital investment. The negative correlation between fertility and education (particularly female education) is well known, but simply looking at this correlation does not immediately provide an estimate of the structural effect of education on fertility. Following [Karra, Canning, and Wilde \(2017\)](#), we use the estimate in [Osili and Long \(2008\)](#), derived from examining the impact of a universal primary education program in Nigeria. [Osili and Long](#) find that an extra year of education reduced fertility by 11%.¹³

Mapping this structural estimate into our framework requires taking a stand on whether the effect of increased quantity of schooling on fertility (which is what they measure) is the same as the effects of increasing other dimensions of human capital that are included in the HDI, specifically school quality and health. Existing literature does not give any guidance on this issue. We assume that indeed the effect of increasing either of these other dimensions is the same as the effect of increasing school years.¹⁴

To get an estimate of the effect of human capital increases on fertility, we start with the estimate from [Osili and Long](#):

$$\frac{\delta \ln(f)}{\delta s} = -0.11 \quad (27)$$

Similarly from the assumption that the Mincerian return to schooling is 8%, we have

$$\frac{\delta \ln(h)}{\delta s} = 0.08 \quad (28)$$

Combining these two expressions, the elasticity of fertility with respect to human capital (for changes in human capital that result from schooling) is $-0.11/0.08 = -1.38$.

We can apply this elasticity to the changes in human capital investment that we examine in the earlier in the paper. The first two columns of [Table 3](#) show the increase in human capital per worker in the year 2050 under the typical and optimistic scenarios, each relative to the baseline, broken down into three country-income groups (we focus on lower and middle income countries because we expect that the economic effects of fertility reduction on income will be very different in upper income countries). Applying the estimates just derived, we can convert these into implied reductions in fertility relative to the baseline in each of these cases, as shown in the third and fourth columns of the table.

The second step is to look at the effect of this reduction in fertility on income and human capital investment. Doing this in a fully dynamic fashion would require a major

¹³In the paper, fertility in the treated cohort is only measured to age 25. The authors point to the strong correlation between early and total fertility among non-treated cohorts to argue that the estimate can be generalized to lifetime fertility. However, to the extent that higher educational attainment leads to a delay rather than a reduction in lifetime fertility, their result may be overstated.

¹⁴If we assumed instead that raising years of schooling affected fertility while increasing school quality and health did not, we would find a lower effect of higher HCI on fertility.

Table 3: Estimates of additional effect of human capital on GDP-per-capita through fertility channel

	Increase in avg human capital per worker in 2050 relative to baseline		Reduction in fertility in 2050 relative to baseline		Increase in avg GDP/cap in 2050 relative to baseline (partial equilibrium)		Increase in avg GDP/cap in 2050 relative to baseline (additional general eq. effect)	
Country income group	<i>Typical</i>	<i>Optimistic</i>	<i>Typical</i>	<i>Optimistic</i>	<i>Typical</i>	<i>Optimistic</i>	<i>Typical</i>	<i>Optimistic</i>
Lower	17.7%	40.9%	-20.1%	-37.7%	14.3%	33.0%	13.8%	25.8%
Lower-middle	11.2%	26.0%	-13.6%	-27.3%	8.9%	20.6%	9.3%	18.7%
Upper-middle	6.4%	15.0%	-8.2%	-17.5%	5.0%	11.6%	5.6%	12.0%

redesign of the model in the paper. That is because, comparing our baseline to the different alternative paths, education is varying on a cohort-by-cohort basis, and we would have to correspondingly adjust the age-specific fertility of each cohort to generate new path of population.

As an alternative, we build off results from an existing macro-demographic model, that of [Ashraf, Weil, and Wilde \(2013\)](#). That paper considers the effects of exogenous reductions in the total fertility rate (TFR) in a model parameterized to match data from Nigeria, which is classified by the World Bank as a lower middle income country. Channels of causation that are modeled (based on well-identified microeconomic evidence) include the effects of lower fertility on the dependency ratio, human capital investment, female labor force participation, child health, and life cycle saving. The specific reduction in fertility considered is from the United Nations medium variant forecast to the low variance forecast. Although the simulation shows the value of income in each five year period, we focus on the 50-year horizon presented in the paper, which corresponds to the years 2060-64. In that period, the TFR is 2.87 under the medium variant forecast and 2.37 under the low variant – a reduction of 17.4%. The corresponding increase in income per capita comparing the low to the medium variant is 11.9%.¹⁵ In the seventh and eighth columns of the table, we apply this same ratio of income changes to TFR changes to the fertility changes that we just derived. For comparison, we also show (in columns five and 6) the direct effect of increased human capital on income per capita that come from our model.

As the table shows, the additional general equilibrium effect resulting from reduced fertility is quantitatively quite significant – indeed, looking across the different country groups, in both the typical and optimistic scenarios, it is almost exactly the same magnitude (and always the same sign) as the direct productive effect of human capital on which we have focused. While we think that this is potentially an important result, we suggest that it should be taken with a grain of salt. First, as noted above, in tailoring results from existing literature to the question at hand, we had to make several strong assumptions, in which we erred in the direction that would have produced a larger effect. Second, we were not able to fully dynamically look at the effect of human capital on fertility on a cohort-by-cohort basis. Instead we had to take several shortcuts. This appears to be an area in which future work could do a better job.

Despite the above-listed shortcomings, the exercise in this section can be used to add some further nuance to results from Section 4. There, we found that, at the margin, devoting an additional percentage of GDP to human capital produced a higher present discounted value of income grains than devoting the same percentage of GDP to physical capital investment. Existing literature has not identified the sorts of additional causal channels from physical capital to income, beyond the direct productivity effect, that we

¹⁵[Ashraf, Weil, and Wilde](#) report that the largest contributor to this increase in income per capita, accounting for 40% of the total, is the reduction in the dependency ratio.

have discussed in the case of human capital. Thus properly taking into these channels would certainly amplify the higher efficacy of human vs. physical capital investment.

6 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, 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 75th percentile of what was observed in the data, world GDP per capita is 12% higher than baseline in 2050, while the rate of \$1.90 poverty 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. While we do not have the structural estimates of causal effects that would allow us to explore all of the possible additional channels and general equilibrium effects resulting from an increase in human capital investment, we were able to leverage existing literature to explore one that seems likely to be important: the effect of higher human capital on fertility. Our tentative analysis shows that accounting for the fall in fertility, as well as follow-on effects of fertility on income per capita and subsequent human capital investment, could as much as double the long-run impact of an initial increment to human capital investment. One channel that we were not able to address at all, but which also might be of significant quantitative importance, is the impact of higher human capital on productivity growth, through education's effect on innovation, transfer of technology from abroad, 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.

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A Appendix

A.1 Differences in results when tertiary education is used

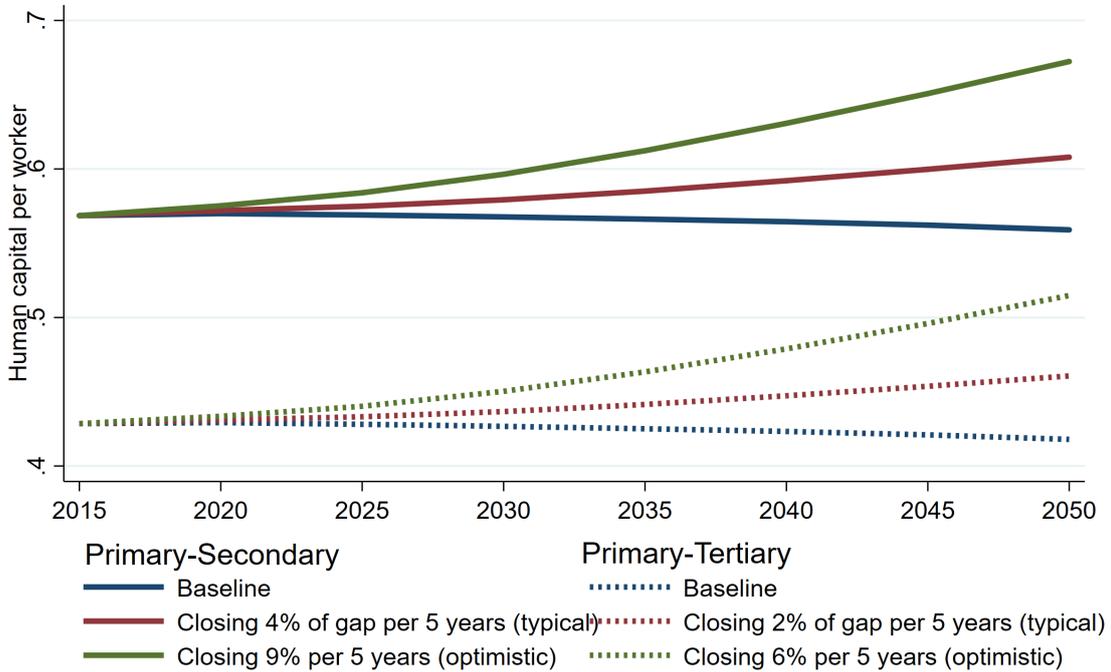
Due to a lack of consistent cross-country data on the quality of tertiary education, the HCI used both by the World Bank and in this paper does not consider education past the secondary level. This section presents results which include data on tertiary to investigate how it might affect the main results of the paper.

To do this, we follow the same process as described in Section 2 for education attainment: we use Barro-Lee data on cohort-specific years of schooling. For this exercise we include tertiary schooling, and for the countries that we supplement with IHME's measure of years of schooling, we only perform the first conversion exercise described above in A.2 to convert IHME primary-tertiary years of schooling into Barro-Lee primary-tertiary years of schooling. We then apply the same learning adjustment as before, assuming the quality of education measure we use also applies to tertiary. For final calculations, a maximum 16 years of schooling is assumed.

In addition to adjusting the years of schooling used to calculate cohort-specific human capital in 2015, we also adjust the calculation of our scenarios to reflect different rates of growth in tertiary education. This presents a challenge: as described in Section 2.3, our scenarios are calculated using median and 75th percentile changes between in the components of the original World Bank HCI between 2005-2015. We then consider how quickly the HCI gap would close if a country with median levels of those components if it experienced the same changes in those components.

The World Bank's HCI uses expected years of schooling, which, as described in (Kraay 2019), are calculated using repetition-adjusted enrollment rates by school level. These rates are "taken from the UNESCO Institute for Statistics, and extensively revised/updated/expanded with estimates provided by World Bank staff." Rather than recreate the World Bank's updated metric of EYS to account for tertiary, which would not take into account revisions made by their staff, we instead combine the existing measure with Barro-Lee's estimate for tertiary schooling. We do this by, for each country, recalculating EYS in 2005 by adding the current version of EYS (Pre-primary through secondary) to the average years of tertiary schooling obtained by 20-24 year olds in the Barro-Lee data. We then recalculate EYS in 2015 the same way by adding the most recent measure of tertiary schooling in Barro-Lee (2010). We then proceed as described in Section 2.3, by calculating the median and 75th percentile change in this tertiary-adjusted EYS. For our last step, when we take our median country, we calculate the final World Bank HCI using a maximum of 18 possible years (Pre-primary through tertiary) rather than 14, and we then calculate the expected reductions in the HCI gap as described above. When we include tertiary schooling in this calculation, our five year reductions in the HCI gap under the typical and optimistic scenarios are 2.3% and 5.6%, respectively. These lower projects reflect both low levels of tertiary growth in the countries in our sample, but

Figure 10: Human capital per worker: original model vs tertiary education model

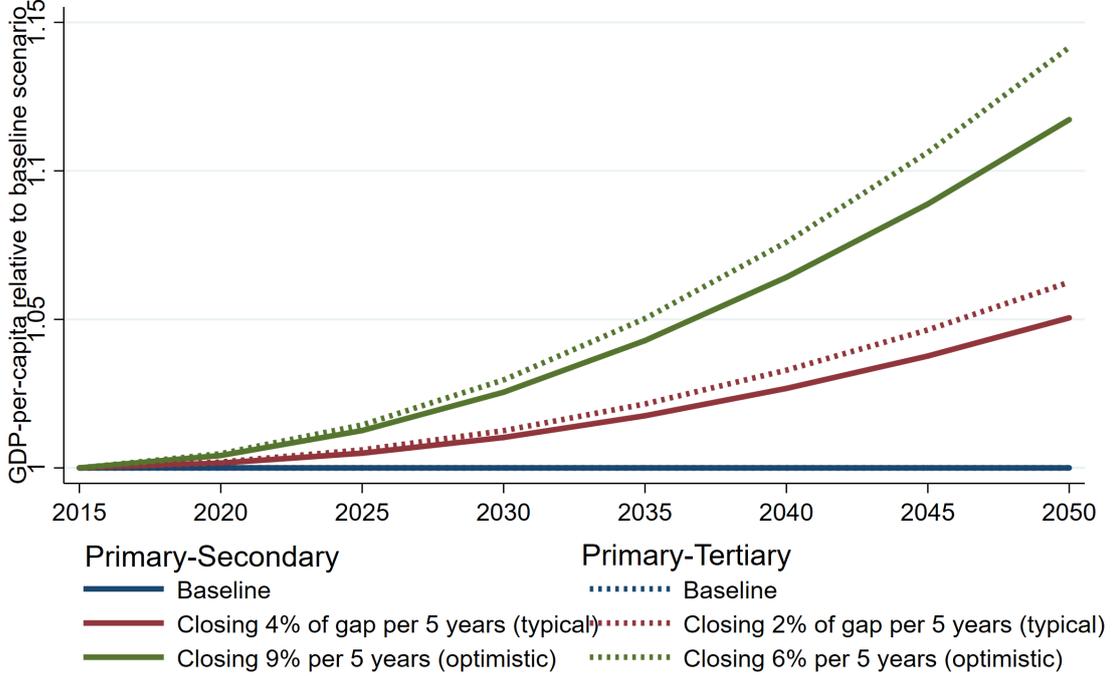


also the mechanical generation of a wider gap, by raising the the total number of possible years of schooling beyond that of secondary.

Figures 10, 11 and 12 display the results for human capital per worker, GDP per capita and \$1.90 poverty for our original model and one which includes tertiary in the manner described above. Mechanically, human capital per worker starts at a lower level in the tertiary schooling model, as raising the maximum possible years of school to reduces the average level of human capital from education (relative to the maximum) observed in the data. Otherwise, subsequent trends in the baseline, typical and optimistic scenarios are broadly similar. Human capital per worker in 2050 is slightly higher relative to the baseline scenario in the tertiary case, driven by the fact that, for a given percent decrease in the HCI gap, the level changes in human capital will be greater for the tertiary model because it starts with a larger gap.

Income growth is slightly faster in the tertiary model. This is driven by two factors. First, as described above, the tertiary model leads to slightly faster rates of human capital growth. Second, as the tertiary model starts with lower levels of human capital, when the model is calibrated for 2015, more weight is placed on initial productivity, leading to higher levels of productivity later on. In the original model, GDP per capita would be 5% and 12% higher in 2050 relative to the baseline, where in the tertiary model GDP per capita would be roughly 6% and 14% higher, respectively. The difference in observed global poverty rates is negligible.

Figure 11: Projected GDP per capita for world: original model vs tertiary education model



A.2 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:

$$EA_{a,n}^{BL,P+S+T} = \alpha + \beta_1 EA_{a,n}^{IHME} + \beta_2 (EA_{a,n}^{IHME})^2 + \varepsilon_{a,n} \quad (29)$$

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

Figure 12: Poverty projections: original model vs tertiary education model

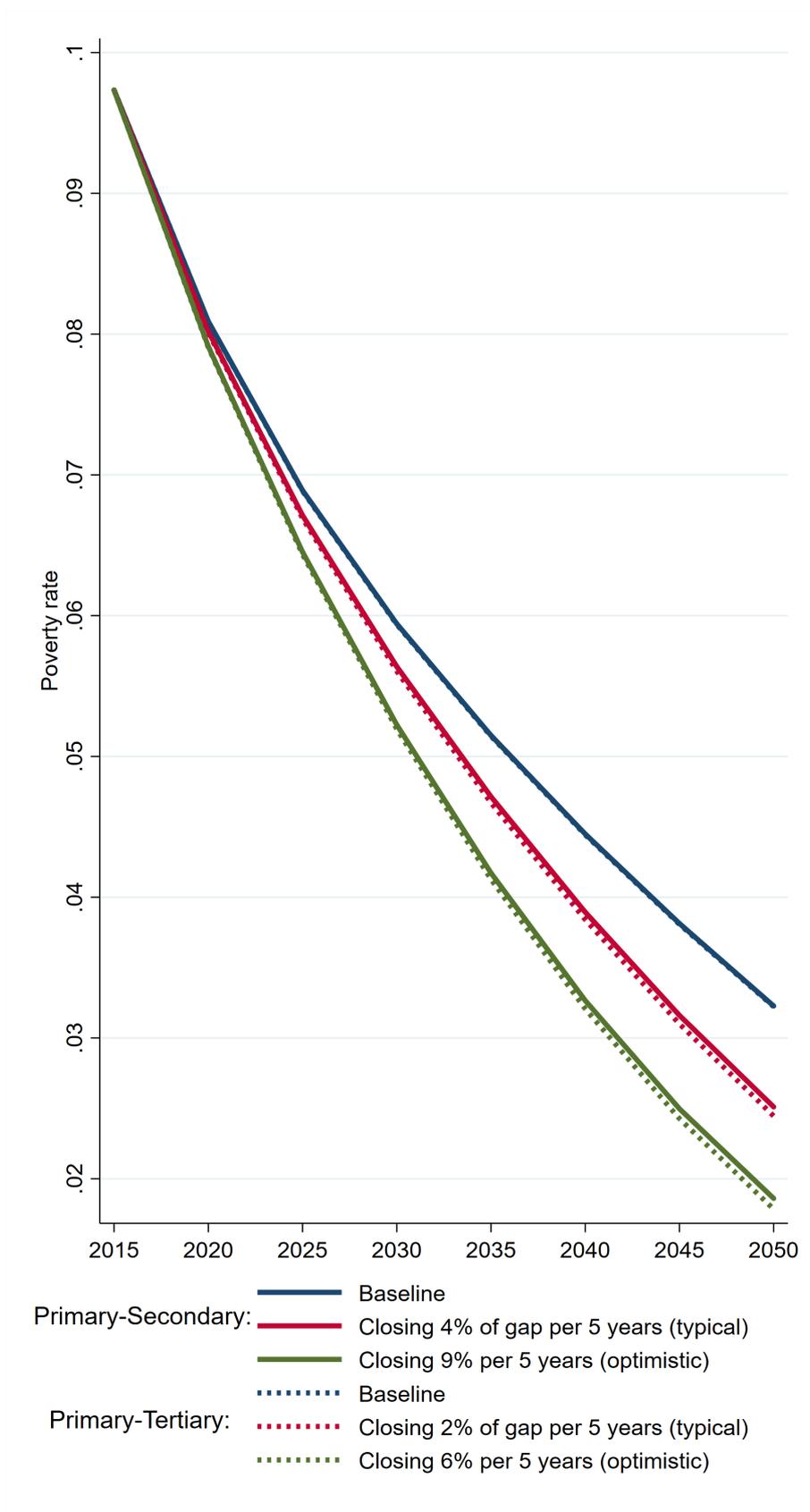
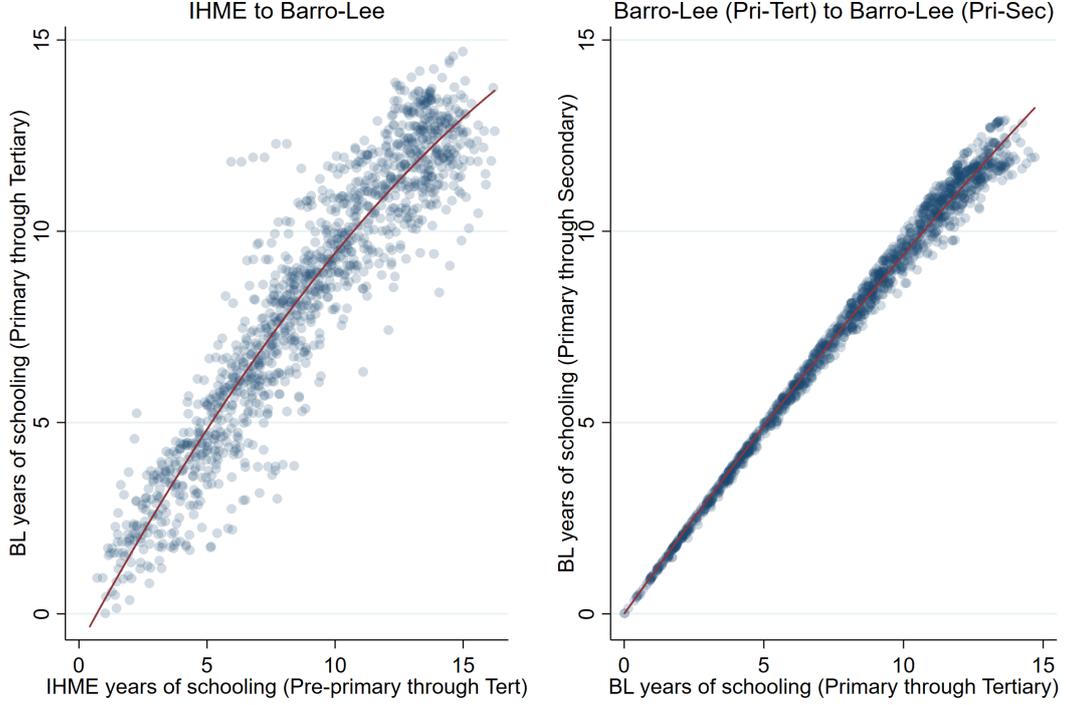


Figure 13: Converting IHME years of schooling (Primary-Tertiary) to Barro-Lee (Primary-Secondary)



Note: red line indicates predicted values from quadratic regression

cohorts from 2010:

$$EA_{a,n}^{BL,P+S} = \lambda_1 EA_{a,n}^{BL,P+S+T} + \lambda_2 (EA_{a,n}^{P+S+T})^2 + \varepsilon_{a,n} \quad (30)$$

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:

$$\widehat{EA}_{a,n}^{BL,P+S} = \lambda_1 \left(\alpha + \beta_1 EA_{a,n}^{IHME} + \beta_2 (EA_{a,n}^{IHME})^2 \right) + \lambda_2 \left(\alpha + \beta_1 EA_{a,n}^{IHME} + \beta_2 (EA_{a,n}^{IHME})^2 \right)^2 \quad (31)$$

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