Accounting for Cross-Country Income Differences Revisited*

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Abstract

Development accounting is the search for proximate sources of large cross-country income differences. This article describes how knowledge in this field has evolved over the last two decades since the influential work of Caselli (2005). There have been large advances in the measurement of production inputs (labor, physical capital, and human capital). These advances have generally raised the estimated contribution of inputs for development accounting, which reduces the importance of the residual total factor productivity (TFP) term accordingly. Our best guess is that inputs account for 45–65 percent of GDP per worker differences, versus 30 percent or less using the classic specification. The literature has also made progress in moving away from Cobb-Douglas production technologies and measuring factors such as public investment and management quality that were previously bundled into TFP. Our review highlights the new implications of these advances, areas where future research would be beneficial, and the limitations of development accounting.

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1 Introduction

One of the central questions of economics is why output per worker varies so much across countries. Development accounting has become a widely used tool for making progress on this question over the last three decades. The main appeal of development accounting is its simplicity: researchers need only the production function and measures of the factors of production to gain insights into the development process.

The main output of development accounting is an estimate of the extent to which factors such as human capital or physical capital can account for cross-country productivity differences. We use the word *account* rather than *explain* because we learn about the proximate sources of productivity differences rather than their root causes. Nonetheless, these estimates are useful guides to researchers and to policy-makers. For example, if physical capital were found to account for all of cross-country productivity differences, that would point to a role for models that explain large capital differences and possibly to policies that promote investment and infrastructure.

It is useful to draw an analogy to the practice of decomposing international differences in life expectancy using data on mortality by cause of death. For example, heart disease is the leading cause of death in advanced economies and a significant killer of those aged 60 and above in low-income countries. Yet the most consequential mortality gaps are for infectious diseases like malaria and treatable conditions like diarrheal disease, which take millions of young lives in the developing world each year and kill virtually no one in advanced economies (Global Burden of Disease Collaborative Network, 2024). Comparisons of statistics like these do not pinpoint the root causes of international mortality gaps, but they do help steer research and policy efforts in low-income countries toward childhood health conditions rather than, say, statin treatments for older adults.

While many studies have helped shape the literature on development accounting, the article by Caselli (2005) has arguably done the most to inspire subsequent research in the field.[1] Hsieh and Klenow (2010) and Caselli (2016) both provide updates, but there has been a great deal of recent research that substantially revises some of the main conclusions in the field. This paper synthesizes this research and also identifies new, promising directions for future investigations.

The main message of Caselli (2005) is that stocks of physical and human capital account for little of the cross-country variation in output per worker. Instead, he attributes

[1] Significant precursors include the seminal work of Mankiw, Romer and Weil (1992) and Young (1995), which concluded that factor accumulation accounted for the bulk of observed economic growth, and Klenow and Rodríguez-Clare (1997), Hsieh (2002), and Hall and Jones (1999) whose approaches assigned a much larger role to total factor productivity.

most of the variation in development to TFP, the residual term taken as exogenous in the exercise. Caselli does not view his conclusion as a success, but rather as a humbling reminder of how much the economics profession still needs to learn, akin to the physics profession's realization that imperceptible "dark matter" constitutes most of the universe's mass. His findings imply that research on economic growth over-emphasized the neoclassical models of capital accumulation that followed from Solow (1956). They reinforce a broader perception that the literature needs new theories of TFP (Prescott, 1998), and have helped spur important quantitative macroeconomic research on such topics as financial frictions, misallocation, and the special role of agriculture.[2]

Much of the new research since his review focuses on improving factor measurement. New measures of working hours only deepen the productivity puzzle by 9 percent: workers in poorer countries actually work longer hours, not shorter ones. The literature has made progress on measuring physical capital along multiple dimensions, including measuring physical capital services, country-specific depreciation rates, and natural capital stocks, such as mineral deposits. These additions and improvements have only negligible effects on the implied importance of physical capital for development accounting. Physical capital accounts for around 5 percent of GDP per worker differences when we use capital stocks or capital services as our measure. It actually falls and turns negative when we consider natural capital, because developing countries are abundant in natural capital. Dividing aggregate capital stocks into public and private components holds promise, but there is substantial uncertainty about the measurement of public capital and about the parameters of the production function that govern its importance.

In contrast, human capital per worker has emerged as a much more important factor than previously thought. Internationally comparable test scores and estimates of the returns to schooling of migrants both point to lower-quality schooling in poorer countries than in richer ones. In other words, it is not just the low average years of schooling that hold down human capital levels in poor countries, but the quality of time spent in the classroom. New survey evidence also shows that workers accumulate less human capital over the life-cycle in poorer countries than in richer ones, which widens the measured gaps in human capital per worker. Workers in developed countries are taller, which is evidence of better health. Our updated calculation suggests human capital accounts for 60-70 percent of cross-country GDP per worker differences. We discuss both the uncertainty in this estimate and the challenge of identifying which components of

[2] See for example the early and influential work of Buera, Kaboski and Shin (2011) on financial frictions, Restuccia and Rogerson (2008) and Hsieh and Klenow (2009) on misallocation, or Restuccia, Yang and Zhu (2008) and Adamopoulos and Restuccia (2014) on agricultural productivity.

human capital account for most of this variation.

As a complementary approach, the literature also uses new data to estimate the effects of switching countries on the wages of international immigrants. What makes immigrants an informative group for study is that they bring their human capital with them but leave their home country's physical capital and TFP behind. Thus, they can provide independent evidence on the extent of human capital gaps. Several papers now document that migrants from developing to developed countries achieve wage gains that, while sizable for the individual, are less than half of the difference in GDP per worker between the source and destination country. This evidence thus provides an alternative deductive way to quantify the role of human capital; it again suggests that human capital can account for roughly 60-70 percent of GDP per worker differences.

A final fruitful area of research incorporates imperfect substitution between low- and high-skill workers with different productivity levels as in Katz and Murphy (1992) into development accounting. This model allows low-skill and high-skill workers to be imperfect substitutes with different productivity levels. Developed countries have higher shares of skilled workers, but not lower skill premia. This is possible because they have more skill-biased technologies and more human capital per skilled worker, with the former doing the lion's share of the work. In total, the imperfect substitutes labor aggregator has the potential to account for a sizable share of GDP per worker differences, but the exact figure is highly sensitive to how substitutable the two types of workers are.

Summing up these many changes leads to a more optimistic conclusion than the one reached by Caselli two decades ago. Combining our new estimates implies that inputs account for 45–65 percent of cross-country GDP per worker differences. By the same metric, the figure in Caselli was just 28 percent. This finding reflects primarily a larger role for human capital: as we noted above, the role of physical capital is roughly unchanged and the role of hours per worker is actually negative. The range of plausible estimates is wide, reflecting the challenge of developing reliable estimates of many potentially important factors. However, the final figure is likely to be higher than was previously thought. This suggests that a shift back towards research on variation in inputs is warranted. The wide range of results suggests the need for research that narrows the range of estimates for some of the most uncertain components, such as the role of public capital or the imperfect substitutes labor aggregator.

While reading this review, it is useful to keep in mind three important limitations of development accounting that are recurring themes in our review. First, development accounting works well when we have external evidence on cross-country differences in production inputs and how to scale the importance of those inputs for production.

When either ingredient is absent, it struggles – as we will see for public investment, for example. Second, development accounting quantifies the proximate sources of cross-country GDP per worker differences. It does not determine the precise reasons why poorer countries today have so much less machinery and equipment than richer ones; nor why their workers are equipped with less knowledge useful for production. Third, it cannot identify the precise policy levers that poor countries can pull to improve their lot. Nonetheless, we argue in the pages below that development accounting is a useful framework for guiding our thinking about the macroeconomics of development.

2 Overview of Basic Structure and Facts

We begin with an overview of the classic development accounting structure, which closely follows Klenow and Rodríguez-Clare (1997), Hall and Jones (1999), and Caselli (2005). We provide updated results for the most recent data.

2.1 Development Accounting Structure

Let the output of country $i \in I$ be given by a common aggregate production function

$$Y_i = F(A_i, K_i, L_i), \tag{1}$$

where K_i is its physical capital input, L_i is its labor input, and A_i is total factor productivity.

Development accounting rests on two simple points. First, if the production function F is known and satisfies standard conditions and if Y_i, K_i, and L_i can be measured, then equation (1) can be solved to yield A_i. Second, it is then possible to quantify the contributions of physical capital, human capital, and total factor productivity to cross-country productivity differences by evaluating their importance using the production function F.

The classic development accounting exercise specializes to the Cobb-Douglas production function

$$Y_i = K_i^{\alpha}(A_i L_i)^{1-\alpha}, \tag{2}$$

which is widely used in macroeconomics. Its main virtue for our purposes is that it is consistent with the fact that factor income shares do not seem to vary systematically with income per capita (Gollin, 2002; Feenstra, Inklaar and Timmer, 2015; Humphries and Weisdorf, 2019).[3]

The sourcing and measurement of the necessary ingredients to implement development accounting have become standardized. Output is measured as purchasing power parity-adjusted gross domestic product (PPP GDP), typically sourced from the most recent version of the Penn World Table (PWT) (Feenstra, Inklaar and Timmer, 2015). Our results use 2023 data from PWT 11.0 (Feenstra, Inklaar and Timmer, 2025). Recent versions of the PWT provide multiple measures of GDP; the RGDPo measure (output-side real GDP) is the most appropriate for development accounting, which seeks to understand differences in productivity.

Physical capital is measured using the perpetual inventory approach, which results in a measure that Pritchett (2000) aptly described as cumulated, depreciated investment expenditures. Researchers used to construct this measure themselves; the procedure for doing so is described in Appendix A.1. Recent editions of the PWT instead include a direct measure of the real physical capital stock (cn), which we use for our results. The construction of this series incorporates several improvements over the classic approach; we describe them in Section 4.

The labor input is constructed as the product of the number of workers, N_i, and the human capital per worker, h_i. Data on the number of workers by country are widely available; we again use data from the Penn World Table. We take up the topic of richer measures of the aggregate labor input in Section 3. Human capital is typically constructed using what is sometimes termed the macro-Mincer approach,

$$h_i = \exp(0.1 \times S_i), \tag{3}$$

where S_i is the average years of schooling in the country. We source data for most countries from the most recent version of the Barro and Lee (2013) data.[4] The underlying logic for this last assumption was developed by Bils and Klenow (2000). If workers are perfect substitutes and markets are competitive, then a worker's wage is proportional to their human capital. A long literature in labor economics dating back to Mincer (1974) establishes that log-wages are roughly linear in schooling, which leads to this functional form.[5]

[3] Christensen, Cummings and Jorgenson (1981) conduct accounting exercises with a translog production function, which weights factor differences between countries by average factor shares. As Hall and Jones (1999) note, given that factor shares are uncorrelated with development, this produces results very similar to simply focusing on a Cobb-Douglas production function from the outset.

[4] We augment this with educational attainment data from World Bank (2026) for countries that are missing from Barro-Lee but are present in the World Bank data. The two series are highly correlated.

[5] Earlier work, including Hall and Jones (1999) and Caselli and Coleman (2006), draws on databases that collected country-level estimates of returns to schooling and experience from published studies (Psacharopoulos, 1994; Psacharopoulos and Patrinos, 2004). Those estimates suggested higher returns to

The output elasticities with respect to capital and labor, α and $1 - \alpha$, are less straightforward to measure than one might think. Given standard assumptions, they can be measured using the factor income shares of capital and labor. The challenge is that national accounts include an additional category of "mixed income," the total income accruing to self-employed workers. This category represents factor payments to both capital and labor (since the self-employed may supply both factors) and is a large share of overall income in many developing countries. Gollin (2002) proposes several possible adjustments and finds that the labor share is roughly two-thirds and is uncorrelated with GDP per capita. We set α to one-third to be consistent with this. Feenstra, Inklaar and Timmer (2015) have re-investigated this topic using similar approaches and more recent data. Their preferred estimate is a labor share that is roughly one-half and uncorrelated with development. As we note below, using this value instead would have only a modest effect in our preferred specification. In either case, once we have chosen α and have measured the inputs, it is then possible to construct A_i for all countries.

From here, the classic literature diverges along two dimensions. The first is how to measure the contributions of A_i, K_i, and L_i. To understand the complication, it is useful to return to the analogy to decomposing mortality by cause of death. One reason why decomposing mortality is straightforward is that all the relevant factors are measured in the same unit: deaths. Total deaths can naturally be decomposed into deaths by heart attack, malaria, car accident, and so forth. The same is not true here: we cannot evaluate the role of physical capital, human capital, and TFP directly, but rather we must use the production function to arrive at the contribution of each.

There are two ways to proceed. The first is simply to divide both sides by N_i to arrive at

$$y_i = k_i^{\alpha}(A_i h_i)^{1-\alpha}, \tag{4}$$

where we use lower-case variables to denote per worker values. The left-hand side of equation (4) is thus GDP per worker; our goal is to decompose cross-country variation in this object into the contributions of capital per worker, k_i, human capital per worker, h_i, and TFP A_i. This first approach weights the contribution of each factor using its output elasticity.

An alternative approach used by Klenow and Rodríguez-Clare (1997) and Hall and Jones (1999) is to express the right-hand side of the development accounting equation in

schooling for countries with lower levels of schooling, so they incorporated that into their construction of h. More recent estimates suggest the return to schooling is around 10 percent per year and is uncorrelated with average years of schooling or development (Banerjee and Duflo, 2005; Caselli, Ponticelli and Rossi, 2016). This choice has little bearing on the quantitative accounting results below.

terms of the capital-output ratio rather than the capital-labor ratio. With some algebraic manipulation, this leads to

$$y_i = \left(\frac{K_i}{Y_i}\right)^{\frac{\alpha}{1-\alpha}} h_i A_i. \tag{5}$$

Changing the expression used to evaluate the role of capital is also associated with a change in the exponents used to evaluate each term. Equation (5) puts a larger weight on human capital and TFP. It follows that it assigns a lesser role to physical capital, although that is not immediately apparent because we have changed both the expression used to measure physical capital and its weight.

Caselli (2005) notes that different approaches to development accounting often address different counterfactuals and answer different questions. When we use equation (4) to study development accounting, we are asking questions such as, "What would be the effect on cross-country productivity differences if all countries had the same TFP, while holding differences in physical capital and human capital per worker at their current, observed levels?" This is in some sense the most direct question to ask when approaching the data, which leads us to include it going forward.

While straightforward to interpret, the decomposition in equation (4) has one drawback. Varying A or h while holding K/N fixed implies large changes in the marginal product of capital. This feature is inconsistent with most models and hence makes the decomposition less useful as a guide to theory than it might be. The decomposition in equation (5) remedies this by re-expressing GDP per worker in terms of the capital-output ratio. Holding the capital-output ratio fixed is equivalent to holding the marginal product of capital fixed, which captures the long-run adjustment built into a wide class of models.[6] Thus, this decomposition is used to ask questions such as, "What would be the effect on cross-country productivity differences if all countries had the same TFP while holding the marginal product of capital fixed?" By incorporating the endogenous adjustment of capital, we are giving greater importance to A and h in the development accounting decomposition.

By contrast, there is less agreement on whether varying A, k, or K/Y induces a change in h. Increasing them certainly raises the marginal product of labor. If markets are competitive, then this also raises wages. However, in the classic model of Becker (1964), higher wages do not lead workers to accumulate more human capital. The

[6]This includes any model in which output and input markets are competitive, so that the marginal product of capital is equal to the user cost of capital, and in which the user cost of capital is held fixed. The latter can be accomplished by appealing to a fixed world interest rate or having interest rates determined by the Euler equation in a closed economy with constant relative risk aversion preferences and a common discount rate.

intuition is that if workers invest only their own time into human capital accumulation, then higher wages raise the opportunity cost and the benefit of acquiring human capital proportionally. Manuelli and Seshadri (2014) and Erosa, Koreshkova and Restuccia (2010) propose models that allow workers to invest a combination of their own time and market-produced goods; these models generate a feedback effect from higher wages to higher human capital accumulation. We view these as theories of the differences in education quality and life-cycle human capital accumulation that we document in Section 5. Alternatively, models with imperfect substitution of labor as in Katz and Murphy (1992) can generate human capital accumulation in response to skill-biased technical change. We return to this point in Section 6.2.

The second dimension over which papers vary is the metric used to evaluate the relative importance of the factors given either equation (4) or (5). We focus on the Klenow and Rodríguez-Clare (1997) metric:

$$\text{share}_x \equiv \frac{\text{cov}(\log(x), \log(y))}{\text{var}(\log(y))}. \tag{6}$$

When evaluating equation (4), the relevant factors are $x \in \{k^\alpha, h^{1-\alpha}, A^{1-\alpha}\}$; when evaluating equation (5), they are instead $x \in \{\left(\frac{K}{Y}\right)^{\alpha/(1-\alpha)}, h, A\}$.[7]

Caselli (2005) focuses on two alternative metrics, $\frac{\text{var}[\log(x)]}{\text{var}[\log(y)]}$ and $\frac{x_{90}/x_{10}}{y_{90}/y_{10}}$, which he labels $success_1$ and $success_2$. He also shows that for the classic development accounting exercises the answer does not depend much on which of the three metrics one uses. Below, we show that the same finding still holds for our updated data when we quantify the role for inputs versus productivity.

We prefer the covariance-based metric because it has two benefits that have become increasingly valuable given the evolution of the literature since Caselli (2005). First, a decomposition that uses $\log(y)$ rather than y, in conjunction with the production function in (2), produces results that are additive and order invariant. This is valuable because research since Caselli (2005) has increasingly tended to study and evaluate the contribution of a single factor in isolation, rather than redo the entire development accounting exercise from scratch. An additive and order-invariant decomposition makes such results more meaningful and portable. Second, a covariance-based decomposition rewards factors that both vary and correlate with output per worker differences. As we will see below, inputs and TFP are both highly correlated with output per worker, so this

[7] An ancillary benefit of this metric is that it can be quantified as the coefficient from regressing $\log(x)$ on $\log(y)$. In line with the literature, we do not weight this regression or any of the other accounting approaches. Our view is that when trying to understand the development process, each country constitutes an observation.

Table 1: The World Income Distribution: Summary Statistics

	GDP per capita	GDP per worker
10th percentile	2,835	7,596
Median	17,784	42,796
Mean	27,740	58,197
90th percentile	62,891	121,293
var[log(y)]	1.40	1.06
90-10 ratio	22.2	16.0

Note: Table reports summary statistics of the world income distribution using GDP per capita and per worker in 2023. GDP is measured in 2021 international dollars. The sample includes 153 countries for which data are available on GDP, physical capital, and years of schooling. Source: Feenstra, Inklaar and Timmer (2025).

was not a concern for the exercises of Caselli (2005). However, more recent research has both studied specific factors and considered a wider range of factors. It is less obvious ex ante that all of these factors are highly correlated with output per worker, which leads us to prefer a metric that naturally keeps track of whether this is the case.[8]

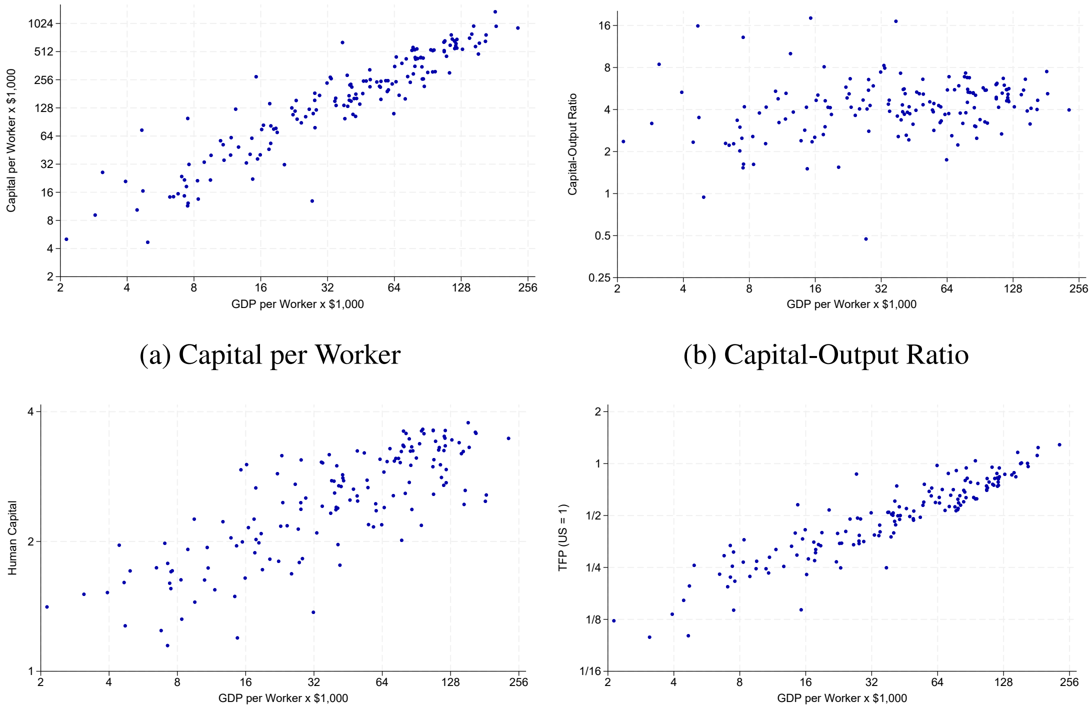
2.2 Summary Statistics and Traditional Accounting Results

With these definitions in hand, we now provide updated development accounting results using the most recent data. We begin with the most traditional measures of physical and human capital stocks, as described above, which correspond closely to the concepts used in Caselli's handbook chapter. In the subsequent sections we incorporate the main developments in the literature since then.

Table 1 reports summary statistics of the world income distribution. We restrict attention to the 153 countries with valid data on GDP, employment, physical capital stocks, and years of schooling. We exclude Venezuela, which currently reports implausibly low GDP per worker figures (less than 15 percent of the GDP per worker of any other country). The remaining countries in total cover 96 percent of the world population and provide extensive coverage of every continent. We use the most recent data:

[8]To give an extreme example, suppose that one identifies a factor that is more prevalent per worker in poorer countries than richer ones. This would imply a positive var$[\log(x)]$ and x_{90}/x_{10}, suggesting that the factor helps account for productivity differences. The covariance metric would instead yield a negative value, rightly indicating that this factor goes in the opposite direction, and is not a promising lead as to what drives productivity differences.

Figure 1: Baseline Development Accounting Inputs



(a) Capital per Worker

(b) Capital-Output Ratio

(c) Human Capital per Worker

(d) TFP

Note: Panel (a) plots physical capital per worker and Panel (b) plots physical capital relative to output. Panel (c) plots human capital per worker, calculated from years of schooling. Panel (d) plots the implied TFP, normalized so that the U.S. TFP is 1. Physical capital and GDP are measured in 2023 and expressed in 2021 international dollars. Source: Feenstra, Inklaar and Timmer (2025), Barro and Lee (2013), and World Bank (2026).

data from 2023 for GDP, employment, and physical capital, and from 2015 for years of schooling.

The two columns give a sense of the cross-country dispersion in GDP per capita (roughly, living standards) and GDP per worker (roughly, productivity). Conventionally, development accounting seeks to understand differences in productivity. The 90-10 ratio for this statistic is 16, indicating substantial variation. Note that the variation in GDP per capita is even larger, with the 90-10 ratio reaching 22.2. The reason is that the number of workers per capita tends to be higher in developed countries. We touch on this point further in Section 3.

Figure 1 plots the classic measures of the inputs to production and the TFP terms implied by equation (2). Panels (a) and (b) plot the two measures of physical capital against GDP per worker. As with all figures for the remainder of the paper, we use log scales for both axes. Panel (a) shows that developed countries have much more

Table 2: Success of Factors, Baseline Measures

Factor	share	std. err.	# countries
Capital-per-worker specification			
Physical capital, k^α	.370	.012	153
Human capital, $h^{1-\alpha}$	.152	.009	153
Human + physical capital	.522	.017	153
Capital-output specification			
Physical capital, $(K/Y)^{\alpha/(1-\alpha)}$	.055	.018	153
Human capital, h	.228	.013	153
Human + physical capital	.283	.025	153

Note: Table reports the share of cross-country differences in GDP per worker that are accounted for by inputs. Results are based on the covariance metric in (6) applied to the capital-per-worker and capital-output specifications in equations (4) and (5). Source: Feenstra, Inklaar and Timmer (2025) and Barro and Lee (2013) augmented with World Bank (2026).

physical capital when we measure it as the capital-labor ratio. The slope of log capital per worker on log GDP per worker is 1.11, meaning that capital per worker rises even more than one-for-one with aggregate labor productivity. Panel (b) shows that the gap between developed and developing countries is much smaller when we measure it as the capital-output ratio; the slope there is just 0.11. Panel (c) shows human capital per worker (measured here, as described above, using data on years of schooling and assuming a constant 10 percent return to a year of schooling). It is also increasing in GDP per worker, though less sharply than physical capital, with a slope of 0.23.

Any hope that factors would account neatly for GDP per worker differences is dispelled in panel (d) of Figure 1, which plots the implied TFP terms. The level of TFP increases robustly with GDP per worker, with a slope coefficient of 0.48. TFP is normalized by the U.S. level. Singapore and Norway, for example, have TFP values that are virtually identical to the U.S. level. China's TFP level is around half the U.S. level. Bringing up the rear of the distribution are Burundi, Yemen, and the Central African Republic, whose TFP levels are just 10 percent of the U.S. level. By any yardstick, the basic accounting in this section relies very heavily on large and mysterious TFP gaps between richer and poorer countries.

Table 2 makes this point more formally by showing the development accounting results. When we apply the covariance metric to capital per worker (equation (4)), we find that physical capital accounts for 37 percent of cross-country productivity differences

Table 3: Success of Factors, Caselli Metrics

Data	$\frac{\text{var}[\log(x)]}{\text{var}[\log(y)]}$	$\frac{x_{90}/x_{10}}{y_{90}/y_{10}}$	# countries
Caselli's data	0.39	0.34	94
Latest data	0.31	0.29	153

Note: Table reports the share of cross-country differences in GDP per worker that are accounted for by inputs. Results are based on the metrics proposed by Caselli, which he labels $success_1$ and $success_2$. Source: first row: Caselli (2005); second row: data from Feenstra, Inklaar and Timmer (2025) and Barro and Lee (2013) augmented with World Bank (2026).

and human capital for 15 percent. Combined, they account for just over half. However, when we apply it to the capital-output ratio (equation (5)), we find much more modest numbers: physical capital accounts for 6 percent and human capital for 23 percent, with a combined total for inputs of 28 percent. The large gap between these two methods has a straightforward interpretation that is consistent with the view outlined in the last subsection that capital-labor ratios can be understood mostly as a response to differences in h or A. Given that the classic method measures small differences in h, we are left to conclude that differences in K/L are mostly endogenous responses to A. This suggests that only around one-quarter of productivity differences can be accounted for by differences in inputs.

The estimated contributions of physical capital and human capital for development accounting are relatively insensitive to the chosen value of α under the capital-output specification (but not under the capital-labor specification). The reason is that in this specification, only the weight on capital depends on a function of α. Further, cross-country differences in the capital-output ratio are modest, so whether we weight them by $\frac{1/3}{2/3} = 0.5$ or $\frac{1/2}{1/2} = 1$ makes little difference.

Table 3 revisits the metrics that Caselli prefers in his overview. The first row shows Caselli's results: he found that the variation in $\log(k^\alpha h^{1-\alpha})$ was just 39 percent of the variation in $\log(y)$ and that the 90-10 ratio in $k^\alpha h^{1-\alpha}$ was just 34 percent of the 90-10 ratio in y. The second row shows the updated results from applying the same metrics to the most recent data, taking us from the 1990s to the 2020s and expanding the sample coverage substantially. The results are somewhat lower, at 31 and 29 percent. Note that when we apply our preferred capital-output specification to the most recent data, we arrive at a very similar figure of 28 percent. The broad agreement between the covariance and the $success$ metrics continues to hold as long as we focus on the total importance of inputs. We include tables summarizing these results for key calculations in Appendix B.1.

Of course, Caselli considered a wide range of possible alternatives. Yet while he expressed caution about certain key choices that he thought bore further scrutiny, the overall message remained essentially unchanged from this simple conclusion. As he memorably put it, “Development accounting is a powerful tool to getting started thinking about the sources of income differences across countries. As of now, the answer to the development accounting question – do observed differences in the factors employed in production explain most of the cross-country variation in income – is: no, way no” (Caselli, 2005, p. 737).

3 Measures of the Labor Input

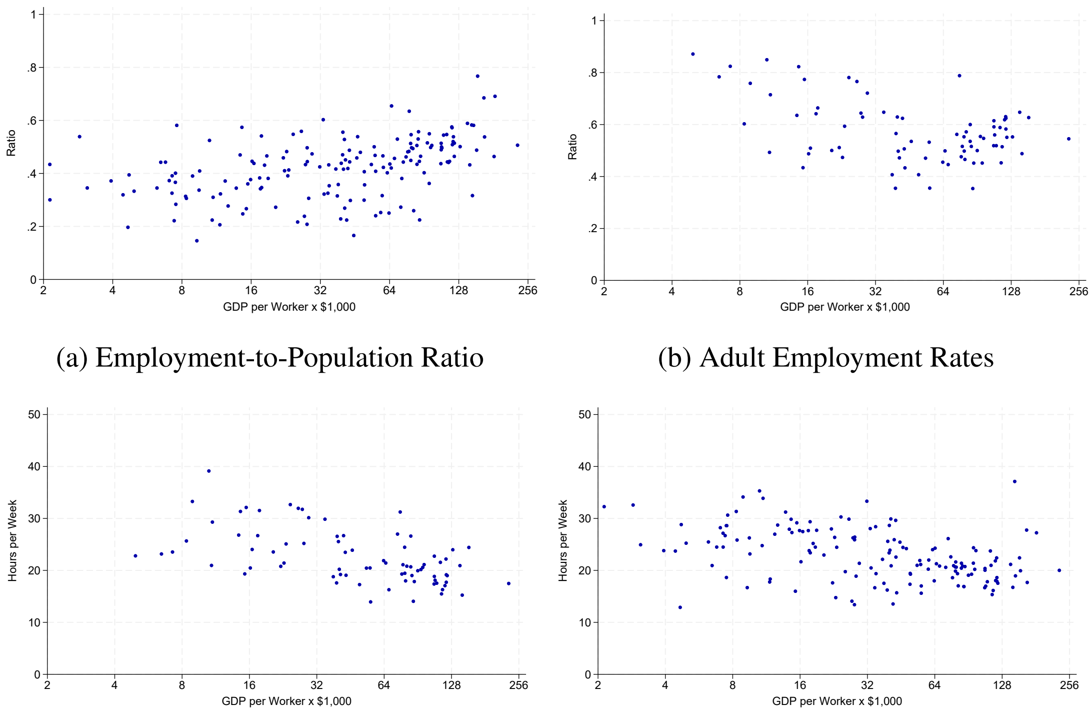
So far we have revisited the classic development accounting setup. We have shown that applying it to the most recent data still yields the familiar result that inputs account for little of cross-country income variation. We now turn our attention to the new insights from the last twenty years of research. We start with the labor input. Could poor countries simply be working less than richer ones?

In one sense, the answer is clearly yes. As we already showed in Table 1, the cross-country gaps in GDP per capita are even larger than those in GDP per worker. It follows immediately that a plot of employment-to-population ratios against GDP per worker indeed shows a robust positive relationship (Figure 2, panel (a)). Employment-to-population ratios average around 0.4 in the bottom quartile of the world income distribution, compared to 0.6 in the top quartile.

These gaps are entirely accounted for by the higher share of children in developing countries, however. To see this, Figure 2, panel (b) plots the *adult* employment rate against development, where adults are defined as those aged 15 and older (Bick, Fuchs-Schündeln and Lagakos, 2018). Adult employment rates are on average higher, not lower, in the world’s least productive countries. Similarly, unemployment rates – which exclude those who are not looking for work – are lower in poorer countries (Feng, Lagakos and Rauch, 2024; Poschke, 2025). This reinforces the practice of focusing on accounting for gaps in GDP per worker; few would argue that insufficient child labor in Africa is a meaningful proximate cause of the continent’s underdevelopment.

Of course, employment rates can mask significant variation in how many hours adults are working in practice. Since the publication of Caselli’s article, many high-quality labor force surveys with information on hours of work have become available thanks to the efforts of international organizations like the World Bank and national statistical offices. Panel (c) of Figure 2 plots the average weekly hours worked accord-

Figure 2: Labor Inputs and Development



(a) Employment-to-Population Ratio

(b) Adult Employment Rates

(c) Average Hours per Adult (Bick et al)

(d) Average Hours per Adult (Gethin-Saez)

Note: Employment-to-population ratios in panel (a) come from the Penn World Table 11.0 and cover the year 2023. Adult employment rates in panel (b) and average hours worked per adult in panel (c) come from Bick, Fuchs-Schündeln and Lagakos (2018). Average hours worked per adult in panel (d) come from Gethin and Saez (forthcoming).

Table 4: Success of Factors Revisited: Labor

Factor	share	std. err.	# countries
Capital-per-worker specification			
Hours per worker, $n^{1-\alpha}$	-.057	.011	139
Capital-output specification			
Hours per worker, n	-.086	.017	139

Note: Table reports the share of cross-country differences in GDP per worker that are accounted for by hours per worker. Results are based on the covariance metric in (6) applied to the capital-per-worker and capital-output specifications in equations (4) and (5). Source: Feenstra, Inklaar and Timmer (2025) and Gethin and Saez (forthcoming).

ing to Bick, Fuchs-Schündeln and Lagakos (2018), who provide hours worked for 80 countries. These data point to higher hours in poorer countries, with adults in the poorest countries working about 50 percent more hours per week than those in the richest countries. Panel (d) reports the estimates of Gethin and Saez (forthcoming), who draw on the most comprehensive set of labor force surveys to date, covering 160 countries, including some very poor and populous nations like Sudan. Their evidence points to a more modest negative relationship between hours and GDP – and, when weighting countries by population, an essentially flat relationship.

Caselli (2005) concluded that lower hours in poor countries were not a promising proximate explanation of international productivity differences. We revisit this conclusion formally in Table 4. There, we augment the set of relevant factors in accounting for cross-country productivity differences to include hours per worker, which we denote by n_i. We evaluate the role of this factor in isolation. As we can see, its contribution is modestly negative in both specifications, which only worsens the development puzzle. Thus, Caselli's conclusion – though speculative, given data quality at the time – turns out to be consistent with current thinking.[9]

There are limits to focusing solely on the cross-country relationship between the labor input and income per capita, however. Each of the data sets highlighted above points to substantial variation in hours worked between countries at similar levels of development, suggesting that labor inputs can help explain low GDP per worker for

[9] One under-explored possibility is that labor effort per work hour could be higher in richer countries. For example, more expensive capital equipment could mean that employers demand more of workers to recoup their fixed costs (Leamer, 1999). More recently, Walker et al. (2024) provide evidence that labor (as well as capital) is under-utilized in less developed economies, which they attribute to integer constraints in input markets.

some countries. For example, Ecuador and Iraq have similar income levels, but the average adult in Ecuador works twice as many hours per week as adults in Iraq. Similarly, the United States and Taiwan average around one-third more hours worked per adult than Italy or Belgium, even though all have similarly high levels of GDP per capita.

Some of this cross-country hours variation is driven by differences in female labor supply, as in the case of Ecuador and Iraq, pointing to important linkages with research on barriers to female labor force participation (see, e.g., Klasen, 2019; Jayachandran, 2021; Gottlieb et al., 2024; Chiplunkar and Kleineberg, 2025). Differences in tax-and-transfer systems can also help explain some gaps in adult labor supply, as in the United States and Italy, for example (see, e.g., Prescott, 2004; Gethin and Saez, forthcoming). Finally, armed conflict must also play a key role in reducing work opportunities in affected countries, such as Afghanistan and Somalia. These and other forces that drive down adult labor supply could indeed be important proximate causes of underdevelopment in some countries.

4 Measurement of Physical Capital

Research in this literature has also made progress in measuring cross-country differences in physical capital inputs. We describe efforts to measure capital services rather than capital stocks; to measure and incorporate natural capital; and to divide capital in various ways. While much of this research effort has improved our measures and understanding of physical capital, we will see that it has done little to change our conclusions about the role that physical capital plays in accounting for cross-country GDP per worker differences. One exception is the measurement and inclusion of public capital, which we find is potentially important but also highly uncertain.

4.1 Capital Services

The classic development accounting exercise equates physical capital with an estimate of the value of the country's physical capital *stock*, which captures the value of its roads and warehouses. Ideally, we would instead use the flow of physical capital *services*, which captures the transportation and storage services delivered in a year. Fortunately, there is a well-known relationship between the two that opens the door to better measurement (Fisher, 1930; Jorgenson, 1963).

Imagine a firm that considers purchasing one unit of a capital good at price p_t. It will use the capital services s_t of this good in production for one period, which causes the capital good to depreciate by a fraction δ. The firm then sells the remaining $(1-\delta)$

units of the capital good in the next period at price p_{t+1}. The firm requires an annual return of r, which reflects its opportunity cost of funds. Then the standard no-arbitrage condition requires that

$$s_t = rp_t + \delta p_{t+1} - (p_{t+1} - p_t). \tag{7}$$

Abstracting from price changes by setting $p_t = p_{t+1}$ yields the familiar relationship $s_t = p_t(r + \delta)$, which clarifies the relationship between the value of a capital good and the value of the services it provides. Applying this equation to aggregate capital stocks, we see that if countries have similar required returns and similar depreciation rates, then it is innocuous to use the value of the physical capital stock because capital services are a constant proportion of the stock.

Recent work by Inklaar, Woltjer and Gallardo Albarrán (2019) argues that neither assumption holds well in practice. They start by imputing the required return for each country such that capital payments plus labor payments exhaust non-resource sector GDP. This approach has the virtue of implying that there are no pure profits or rents, so that the data treatment is consistent with the typically maintained assumption of perfect competition. It implies that developing countries have higher required rates of return, which implies a higher capital service flow from a given stock.

Their measurement of depreciation builds on ongoing work by researchers affiliated with the Penn World Table that decomposes investment, physical capital, and depreciation rates for different types of capital goods. This work dates to Inklaar and Timmer (2013), who study six types of capital goods. Subsequent work expanded this to nine types used in Inklaar, Woltjer and Gallardo Albarrán (2019). They estimate a common worldwide depreciation rate for each type of capital good. Differences in each country's depreciation rate then stem from differences in the composition of each country's capital stock. The United States boasts a higher share of software and information equipment than Paraguay or Pakistan; these capital goods depreciate at a higher rate. This logic leads Inklaar, Woltjer and Gallardo Albarrán (2019) to conclude that developing countries have lower depreciation rates, which implies a lower capital service flow from a given stock.

In practice, the higher required return and lower depreciation rates in developing countries roughly offset. Their work is now available in the Penn World Table as capital services (ck). In Table 5 we compare the development accounting results if we use the traditional measure of capital stocks (available as cn) or the newer, more appropriate measure of capital services. The share of GDP per worker differences accounted for by physical capital remains essentially unchanged.

However, we see at least three places where additional research would be beneficial. First, it would be useful to develop additional or alternative evidence on the required returns in different countries. Second, it would be useful to investigate depreciation rates, which are currently assumed to be the same for a given type of capital good across countries. For example, Caunedo and Keller (2021) and Graff (2026) develop evidence that the rate of depreciation for tractors, motorcycles, and food-processing equipment varies by country. Future research in this area would be valuable, particularly approaches that consider depreciation as an endogenous process, as in the models of McGrattan and Schmitz Jr. (1999) and Graff (2026).[10]

Finally, returning to equation (7), Inklaar, Woltjer and Gallardo Albarrán (2019) also incorporate changes in capital goods prices into their measure of capital services. This adjustment can be substantial for categories such as software or information and communication equipment that experience rapid price declines. However, it raises the question of why capital good prices decline beyond what depreciation implies, and whether that decline reflects a fall in the flow of services the good delivers or only in the value of that flow. Thinking through these issues likely requires models with different types or vintages of capital and imperfect substitution across capital goods (see e.g. Caunedo and Keller, 2021). Given the importance of price declines for key capital goods, further progress in this area would be welcome.

4.2 Natural Capital

Another area of progress is the measurement of *natural capital* (as opposed to *reproducible capital*). In short, natural capital refers to land and all its naturally occurring (and economically relevant) features, such as underground petroleum, forests, and croplands. Reproducible capital refers to the oil rigs, lumber mills, and tractors that help transform natural resources into outputs that are valued by consumers. Clearly the cropland – and not just the tractor – determines a farmer's grain output. Yet standard measures of the capital stock, such as those available via the Penn World Table, exclude natural capital entirely. Why? As Inklaar and Timmer (2013) put it: "This is not an assessment that these assets are not relevant, but rather that consistent measurement of the stock of these assets and their value is challenging, even for a single country."

[10] Inklaar and Timmer (2013) also focused significant attention on the high relative price of investment goods to consumption goods in poorer countries apparent in earlier versions of the Penn World Table (Hsieh and Klenow, 2007). This pattern led to investment-good-specific price deflators that differed from the aggregate PPP deflator, and implied relatively larger aggregate capital stocks in poorer countries. Data from the latest version of the Penn World Table, however, show that the relative price of investment goods to consumption goods does not vary significantly with GDP per capita. Why this pattern changed over the last two decades remains unknown.

Table 5: Success of Factors Revisited: Physical Capital

Factor	share	std. err.	# countries
Capital-per-worker specification			
Physical capital stock (cn)	.370	.012	153
Physical capital services (ck)	.367	.011	133
Reproducible capital	.281	.009	128
Natural capital	.015	.014	128
Capital-output specification			
Physical capital stock (cn)	.055	.018	153
Physical capital services (ck)	.051	.016	133
Reproducible capital	.034	.014	128
Natural capital	-.089	.021	128

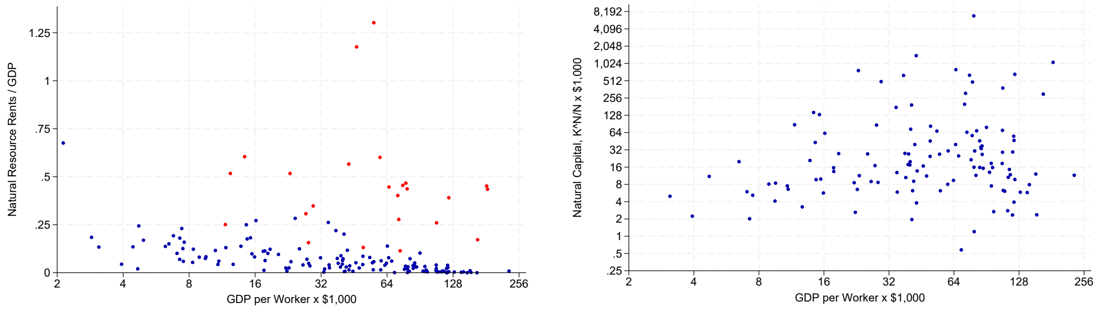
Note: Table reports the share of cross-country differences in GDP per worker that are accounted for by various measures or components of physical capital. Results are based on the covariance metric in (6) applied to the capital-per-worker and capital-output specifications in equations (4) and (5). Source: Feenstra, Inklaar and Timmer (2025) for physical capital stock (cn), physical capital services (ck), reproducible capital, and GDP per worker, and Monge-Naranjo, Sánchez and Santaeulàlia-Llopis (2019) for natural capital.

The seminal paper by Caselli and Feyrer (2007) set about trying to measure the marginal product of capital at the country level in order to gauge whether there could be significant gains (in principle) from reallocating capital from nations with low marginal products to nations with high marginal products. Their work utilizes new data from the World Bank that provide estimates of the natural capital stock and rent flows from natural capital for countries worldwide. Their estimates include the value of underground resources (including petroleum), forest land, cropland, and pasture land. Urban land is excluded, as is land valuable for tourism, such as beaches or other scenic areas.

The main finding is that developing countries tend to have slightly *higher* natural capital stocks, whether measured on a per-worker basis or in proportion to output. Because of this, incorporating natural capital makes the development puzzle slightly harder to explain. Recent work by Monge-Naranjo, Sánchez and Santaeulàlia-Llopis (2019) makes a persuasive case for preferring data on natural capital rent flows to the natural capital stock data used by Caselli and Feyrer (2007). Nonetheless, this finding does not overturn the conclusion that natural capital is more abundant in developing countries. Figure 3 shows why this is the case. Panel (a) follows Monge-Naranjo, Sánchez and Santaeulàlia-Llopis (2019) and plots natural resource rents as a share of GDP against GDP per worker. We differentiate oil exporters (shown in red) from non-oil exporters (shown in blue).[11] Natural resource rents are small for non-oil countries

[11] Oil exporters are specifically defined as countries with subsoil rents that are greater than 10 percent

Figure 3: Natural Resource Rents and Stocks



(a) All countries

(b) Natural capital, K_i^N/N_i

and their share in GDP is uncorrelated with GDP per worker. Panel (b) shows the implied natural capital stock per worker, which again is not strongly correlated with GDP per worker.

We calculate the importance of natural capital as follows. Following Caselli and Feyrer (2007), we treat the Penn World Table capital stock as reproducible capital, and we use the natural-resource rent shares of Monge-Naranjo, Sánchez and Santaeulàlia-Llopis (2019) to calculate an imputed natural capital. We hold the total capital share $\alpha = 1/3$ fixed as in the classic development accounting exercise. We also use the data of Monge-Naranjo, Sánchez and Santaeulàlia-Llopis (2019) to estimate the cross-country average factor share of natural resources η. We set the output elasticity for natural capital to η and the output elasticity for reproducible capital to $\alpha - \eta$. Note that the data point to substantial heterogeneity in the factor share of natural resources across countries (unlike α). We abstract from this because development accounting is not well-defined when countries are assumed to have different production functions.[12] This fact explains why existing work tends to focus on gaps in the marginal product of reproducible and natural capital, rather than performing development accounting. Nonetheless, this assumption allows us to provide some useful calculations that illustrate the key point here.

Table 5 reports the implied results for development accounting. Accounting for natural capital *reduces* the role for capital in development accounting, which we can see by comparing reproducible + natural capital to the physical capital stock or services. The intuition for this result is twofold. First, natural capital itself is only weakly correlated with development, so it accounts for a negligible share of productivity differences in the

of GDP.

[12] One alternative approach would be to allow for a production function that has variable factor shares, such as constant elasticity of substitution (CES). We discuss one example of such an approach in a different setting in Section 7.2.

capital-per-worker specification and actually accounts for a negative share in the capital-output specification. Second, accounting for natural capital leads us to assign a lower weight to reproducible capital, which does vary substantially across countries. Overall, this exploratory adjustment reinforces the message of the preceding discussion. Natural capital is important for interpreting measured capital in resource-rich economies, but it does not account for the productivity advantage of richer countries, which mainly operates through reproducible capital.

4.3 Public and Private Capital Stocks

The trenchant article by Pritchett (2000) argued persuasively that public expenditures on capital are translated less effectively into actual stocks of capital in poorer countries than in richer ones. Poorer countries, in other words, have more bridges to nowhere, more school buildings that were started but never finished, and a greater fraction of public funds siphoned off before they ever reach the project. The implication is that poorer countries have even smaller stocks of physical capital than suggested by calculations that add up private and public investment expenditures assuming a 1:1 translation into public capital stocks.

Caselli's original article (and much of the subsequent literature) incorporated this idea into development accounting by proposing the following law of motion for public capital for each country i:

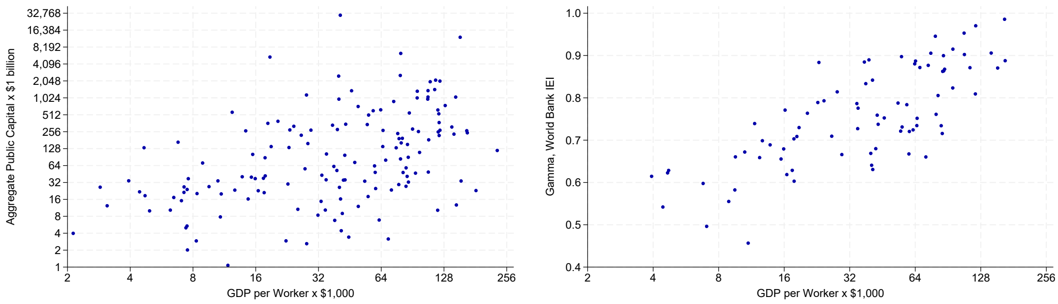
$$K^G_{i,t+1} = K^G_{i,t}(1 - \delta^G) + \gamma_i I^G_{i,t} \tag{8}$$

where δ^G is the common depreciation rate on public capital stocks, $I^G_{i,t}$ is measured public investment, and γ_i is the efficiency with which country i translates public spending into usable public capital stocks. However, there were at that time no data on public investment and no estimates of the efficiency of government investment, so Caselli was unable to provide a precise quantification.

Progress has been made on both issues. Cubas (2020) combines data from multiple sources to develop novel estimates of public investment for 90 countries worldwide.[13] He cumulates these into estimates of public capital and uses them for development

[13] The literature has also explored other divisions of physical capital, including equipment versus structures (Mutreja, 2014; Choi and Lee, 2026) or different types of equipment (Caselli and Wilson, 2004). Decomposing physical capital further would seem a promising avenue for future research. It is natural to suspect that developed countries enjoy larger stocks of specific capital goods such as information and communication equipment, software, or intellectual property. These types of equipment are arguably particularly important for modern production in a way that transport equipment might not be (Casal and Caunedo, 2025). A key challenge to further progress is measurement, particularly the development of disaggregated PPPs.

Figure 4: Public Capital and Public-Capital Efficiency



(a) Aggregate public capital

(b) Public-capital efficiency

Note: Public capital data are from Cubas (2020), public-investment efficiencies γ_i are from the World Bank Infrastructure Efficiency Index (Devadas and Pennings, 2018), and GDP per worker data are from Feenstra, Inklaar and Timmer (2025).

accounting; we describe his results below.

A number of research teams have made progress at quantifying the efficiency of public investment, which is naturally of broader interest. Dabla-Norris et al. (2012) first constructed a "public investment efficiency index" for 70 low- and middle-income countries using country-specific reports related to public investment processes and outcomes. Their estimates point to lower efficiency in developing countries, but they are ordinal. Two subsequent efforts have produced cardinal measures. Devadas and Pennings (2018) develop a measure of efficiency based on the wastage and loss in roads, water, and electricity. Kapsoli, Mogues and Verdier (2023) use stochastic frontier analysis that focuses on the link between public expenditures (in nominal terms) and specific real outcomes: transportation (kilometers of paved roads and railways), energy (kWh of electricity consumption), and health and education infrastructure (secondary school teachers and hospital beds per capita). By narrowing the scope of public capital to key forms of infrastructure, both papers are able to provide cardinal measures that reveal large differences in the public capital delivered by public investment.

Figure 4 shows that the new measures of public capital and public-investment efficiency have potential as contributing factors to cross-country productivity differences. Panel (a) shows that there are large differences in public capital, which captures such critical infrastructure as roads and courts. Panel (b) shows that public investment appears to be much more efficient in developed countries; roughly half of public investment in the least productive countries appears to generate no actual public capital according to this measure.

With these data in hand, we confront a critical question: how does public capital enter the aggregate production function? Public capital is distinct from private capital:

the former captures ports, roads, police stations, and courts, whereas the latter includes factories and trucks. One could compute the "aggregate capital stock" by summing the two, but it is not clear that this object has any meaning. Instead, we follow Cubas (2020) and research dating back to Barro (1990) and Baxter and King (1993) that treats public and private capital stocks as separate, complementary inputs to the production process.

A common specification of the aggregate production function incorporating these complementarities is:

$$Y_i = (K_i^G)^{\zeta}(K_i^P)^{\alpha}(A_i L_i)^{1-\alpha}. \tag{9}$$

where K_i^G and K_i^P are public and private capital, and the parameter ζ is the elasticity of output with respect to public capital. The World Bank, for example, currently uses this production function to simulate the long-run growth impacts of various policy changes involving public investment (see Devadas and Pennings, 2018). Note that this specification posits constant returns to scale in private factors of production and increasing returns to all factors.

We use equation (9) to provide some calculations outlining the potential importance of public capital for development accounting. However, we stress that there is still substantial uncertainty in these calculations and that we view them mostly as a progress update and a marker showing that this area would benefit from additional research. There are two main forms of uncertainty. First, equation (9) embeds a number of assumptions that would benefit from additional scrutiny. For example, it abstracts from the possibility of congestion of public capital.[14] The Cobb-Douglas functional form imposes a particular degree of complementarity between public and private capital. Although this assumption is not immediately implausible, more evidence on the relevant elasticity would be useful.[15] Second, even if equation (9) holds, there is little consensus about the value of ζ, the elasticity of output with respect to public capital. A commonly cited review article by Bom and Ligthart (2014) provides a range of estimates, though these mostly predate the credibility revolution in economics (Angrist and Pischke, 2010), and only 7 percent of estimates pertain to low- or middle-income economies. It is challenging to find plausibly exogenous variation in core public goods like "the rule of law" that one might think of as being the most complementary to private investment. As such, most attempts to estimate ζ have focused on transportation infrastructure, effectively

[14] Cubas (2020) also considered a version that allowed public goods to be only partially non-rival, as in the model of Glomm and Ravikumar (1994). This version reduces the importance of factors in accounting for productivity differences but still leaves them larger than when assuming perfect substitution between public and private capital.

[15] An, Kangur and Papageorgiou (2019) provide the only estimate of the elasticity of substitution between public and private capital, finding a value around 3.

restricting attention to "the area under the lamppost."

With these caveats in mind, we provide some illustrative calculations in Table 6. The first row of this table isolates the role for private capital. The remaining rows estimate the role for public capital using equation (9) under various assumptions about the key parameters – the efficiency of public investment, γ_i, and the elasticity of output with respect to public capital, ζ. In each case, the data for public capital come from Cubas (2020). For the second row we follow Cubas (2020) and set $\gamma_i = 1$ for all countries, abstracting from differences in the efficiency of public investment. We also follow him by setting $\zeta = 0.1$, which is an intermediate value in the literature. This row already implies a non-trivial role for public capital, particularly under the capital-output specification.

For the third row we incorporate differences in the efficiency of government spending γ_i. We take the values from Devadas and Pennings (2018).[16] Allowing for differences in the efficiency of government spending raises the role for public capital only modestly. The intuition for this finding is that the public capital stock in the average developed country is roughly two orders of magnitude larger than that of the average developing country (Figure 4, panel (a)). Incorporating the finding that public investment in developing countries is half as efficient as in developed countries (Figure 4, panel (b)) has a small marginal effect. Finally, the fourth row explores a larger value of $\zeta = 0.20$ that is toward the upper end of what is used in the literature. The role for public capital in development accounting scales with ζ, so this doubles the implied share. In this calculation, public capital accounts for 19–28 percent of GDP per worker differences, and capital as a whole accounts for 39–59 percent of GDP per worker differences.

Caselli's original article concluded that the split between public and private capital was "potentially quite important" in helping to account for productivity differences. Twenty years later, the most natural conclusion is still that this split is "potentially quite important." However, new data have made this case stronger. Moreover, the constraints that hold back firmer conclusions have evolved. Research in this area could benefit greatly from new well-identified estimates of the output elasticity of public capital, particularly in low- and middle-income countries. The same is true of the elasticity of substitution between public and private capital stocks. Future progress in this area seems most likely to come through applied microeconomic analyses of public capital that can shed light on these two elasticities. With such evidence, the importance of physical capital stocks in accounting for international productivity differences should

[16] We impute γ_i for countries with missing values by regressing γ_i on $\log(y_i)$ and using the fitted values. See also Gupta et al. (2014) for work incorporating public investment efficiency into development accounting.

Table 6: Success of Factors Revisited: Public and Private Capital

Factor	share	std. err.	# countries
Capital-per-worker specification			
Private capital, $(k_i^P)^\alpha$	.404	.012	141
Public capital, $(K_i^G)^\zeta$, $\zeta = 0.10$	.082	.014	141
Public capital, $(\gamma_i K_i^G)^\zeta$, $\zeta = 0.10$	.094	.014	141
Public capital, $(\gamma_i K_i^G)^\zeta$, $\zeta = 0.20$	.189	.027	141
Capital-output specification			
Private capital, $(K_i^P/Y_i)^{\alpha/(1-\alpha)}$	.106	.018	141
Public capital, $(K_i^G)^{\zeta/(1-\alpha)}$, $\zeta = 0.10$	.122	.020	141
Public capital, $(\gamma_i K_i^G)^{\zeta/(1-\alpha)}$, $\zeta = 0.10$	.142	.021	141
Public capital, $(\gamma_i K_i^G)^{\zeta/(1-\alpha)}$, $\zeta = 0.20$	.283	.041	141

Note: Table reports the share of cross-country differences in GDP per worker that are accounted for by private and public capital under various parameterizations of the production function. Results are based on the covariance metric in (6) applied to the capital-per-worker and capital-output specifications in equations (4) and (5). Source: Cubas (2020) for public capital and Feenstra, Inklaar and Timmer (2025) for private capital and output per worker.

come more sharply into focus.

4.4 Intangibles

Another missing component of the capital stock series commonly used by macroeconomists is intangible capital. The advertising expenditures that make consumers think of (and buy) specific products could be considered investments in intangible capital. So could expenditures on research and development, which create new goods or refine existing production processes. One can measure advertising and R&D flows using firm-level data, at least in principle. A key issue is how to infer depreciation rates for intangibles. Few jingles stay in the consumer's head forever, and new products tend to have highly variable half-lives.

Corrado, Hulten and Sichel (2009) use time-series evidence from the United States to conduct growth accounting exercises illustrating the importance of intangibles. Their estimates imply that intangible stocks are large and of the same order of magnitude as tangible capital stocks. They conclude that capital accumulation accounts for a significantly larger share of U.S. growth once intangibles are included.

It is not known whether intangibles help explain a larger fraction of income differences across countries. The missing ingredient so far has been aggregate information about expenditures on intangibles. The 2008 revision of the System of National Accounts directed countries to classify some forms of expenditures on intangibles into investments, but progress in developing countries has been uneven. This is a natural topic for future research, and one could imagine that intangibles play a much more significant role in advanced economies. If so, capital per worker gaps would be even larger, and factors would account for even more than they currently do.

5 The Constructive Approach to Human Capital

The classic development accounting exercise outlined in Section 2 equates human capital with the value of years of schooling.[17] One strand of the literature expands the measurement of human capital to include other relevant dimensions, such as education quality and experience.[18] We sum across these dimensions to arrive at a new measure of each country's human capital stock, which leads us to label this the constructive approach. An advantage of the constructive approach is that it provides suggestive guidance on the dimensions of human capital that may be important in accounting for cross-country GDP per worker differences. We organize this section by the dimension of human capital considered. We summarize the role of the various dimensions for development accounting in Table 7.

5.1 Education Quality

A natural starting point for extending the traditional measure of human capital is to incorporate education quality. This is also an area where the raw material for development accounting is in ample supply. Several internationally standardized achievement testing programs evaluate students at a common grade (thus holding the quantity of education fixed) across a wide range of countries.[19] The largest and best-known of these are the OECD's Programme for International Student Assessment (PISA) and the International Association for the Evaluation of Educational Achievement's Trends in International Mathematics and Science Study (TIMSS), but there are also a number of regional testing programs.

Few developing countries participate in a typical round of PISA or TIMSS. In order

[17] The labor literature dating back at least as far as Mincer (1974) understood that multiple dimensions of human capital affected wages. Early work in development accounting considered these other dimensions, but concluded that they played a small role for development accounting. We discuss below why recent research has revised these conclusions.

[18] See also Rossi (2020) for a review that focuses on recent developments in human capital with a broader methodological perspective.

[19] Some programs study students at a fixed age; properly speaking, these results should be purged of differences in grade-for-age progression. Differences in performance due to length of the school year or attendance rates are captured as education quality by this metric.

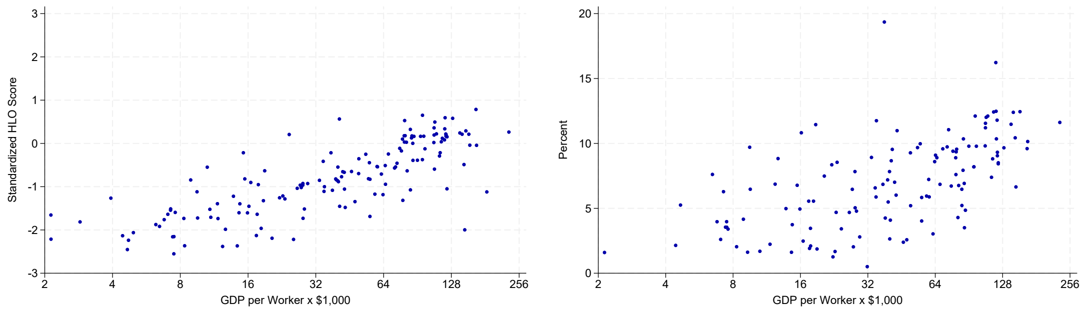
Table 7: Success of Factors Revisited: Human Capital

Factor, x	share	std. err.	# countries
Capital-per-worker specification			
Years of schooling	.152	.009	153
... + schooling quality (test scores)	.240	.012	142
... + schooling quality (immigrants)	.238	.019	123
Experience (non-migrants)	.102	.017	109
Experience (immigrants)	.153	.033	65
Health	.063	.006	152
Human capital (years + quality + experience + health)	.432	.025	106
Capital-output specification			
Years of schooling	.228	.013	153
... + schooling quality (test scores)	.360	.018	142
... + schooling quality (immigrants)	.357	.029	123
Experience (non-migrants)	.153	.025	109
Experience (immigrants)	.230	.049	65
Health	.095	.009	152
Human capital (years + quality + experience + health)	.648	.037	106

Note: Table reports the share of cross-country differences in GDP per worker that are accounted for by inputs. Results are based on the covariance metric in (6) applied to the capital-per-worker and capital-output specifications in equations (4) and (5). Sources, by row: (1): Barro and Lee (2013) augmented with World Bank (2026); (2): Harmonized Learning Outcomes from Angrist et al. (2021), valued at 20 percent per standard deviation; (3): own estimates following Schoellman (2012); (4): Jedwab et al. (2023); (5): Lagakos et al. (2018*a*); (6): height at age 19 from NCD-RisC (2020, 2026), converted into human capital following Weil (2007). Throughout, GDP per worker is taken from Feenstra, Inklaar and Timmer (2025).

to assemble a database covering a large share of the world income distribution, it is necessary to develop a methodology to chain together test scores from different years and testing programs (which implicitly assumes that education quality is constant over time within a country). Angrist et al. (2021) develop an approach that compares results across testing programs using countries that participate in both programs. Their approach allows them to incorporate results from regional testing programs, which greatly expands the number of developing countries with standardized test score data. Their Harmonized Learning Outcomes (HLO) database is the source of the test score results we show here and is the most useful for cross-country researchers because it covers 164

Figure 5: Education Quality Measures



(a) Average HLO Score

(b) Immigrant Returns to Schooling

Note: Panel (a) reports a standardized average HLO score from 142 countries, and Panel (b) reports the returns to origin-country schooling among U.S. immigrants from 123 countries. Source: Angrist et al. (2021) and authors' calculations using the U.S. American Community Survey.

countries in total.[20]

These testing programs consistently point to large gaps in test scores between developing and developed countries. We standard normalize each country's average test score by the OECD mean and standard deviation and plot this normalized test score against GDP per worker in Panel (a) of Figure 5. While some developed countries report an average score that is nearly one standard deviation above the OECD mean, many developing countries report an average score that is more than two standard deviations below the OECD mean. This gap points to very little overlap in the distribution of test scores in the richest versus the poorest countries in the world.

We need to assign these test score differences an economically meaningful scale to incorporate them into development accounting. Broadly, the literature has followed three approaches to doing so. The first and most common approach extends the macro-Mincer approach, which leverages the fact that many microeconomic studies evaluate the log-wage returns to both years of schooling and test scores simultaneously. The estimates of these studies allow us to construct a measure of human capital that extends equation (3),

$$h_i = \exp(0.1 \times S_i + \rho Q_i), \tag{10}$$

where Q_i is the average test score in country i and ρ is a measure of the log-wage return to test score.

[20]See also Patel and Sandefur (2019), who administered a common test containing questions from multiple tests and use it to develop a "Rosetta Stone" that facilitates comparison across testing programs.

The main question is what value of ρ to use. Hanushek, Ruhose and Woessmann (2017) review the relevant literature and conclude that the plausible range runs from 9 to 19 percent. They argue that returns tend to grow over the life-cycle and that the returns measured at later ages are more appropriate, leading them to use $\rho = 0.17$. Angrist et al. (2021) use a slightly higher value of $\rho = 0.2$. The two papers find broadly similar development accounting results: education quality accounts for roughly the same share of cross-state and cross-country differences as years of schooling.

Kaarsen (2014) proposes a second approach to providing an economically meaningful scale for test scores. His approach leverages the fact that the 1995 round of the TIMSS program gave the same test to students in adjacent grades – for example, in 3rd and 4th grade, or in 8th and 9th grade. Intuitively, this allows him to measure education quality as the change in average test scores during one year of schooling. He shows that the rate of test score improvement is roughly uncorrelated with initial test score level but declines with years of schooling. This leads him to propose a test score production function

$$T_{i,S} = \beta + \gamma \log(SQ_i).$$

The parameters β and γ are common across countries, while Q_i is country i's education quality, which governs how much test scores improve with each year of schooling. He finds that a year of schooling in the most productive countries (South Korea, Singapore) generates roughly five times as much test score improvement as a year of schooling in the least productive countries (Yemen, South Africa). He constructs estimates of the stock of human capital by country and once again finds that the variation due to education quality is roughly of the same magnitude as the variation due to education quantity.

An alternative approach to quantifying cross-country differences in education quality uses the information provided by international migrants. This approach originates from the foundational work of Hendricks (2002) and, as we will see below, is now widely used in the literature. A common application studies immigrants from many source countries working in a single destination. Intuitively, studying workers from many countries in a single destination is useful because it holds any destination-specific factors, such as capital-output ratios and TFP, fixed. We can then attribute differences in worker outcomes such as wages to differences in human capital. However, this useful information comes with the drawback that migrants are generally non-randomly selected and their outcomes may be affected by difficulties with skill transfer or discrimination. Papers that pursue this approach seek to leverage the information while mitigating the concerns about selection and skill transfer as much as possible.

Schoellman (2012) estimates the returns to schooling of foreign-educated immigrants in the United States. We re-estimate his main specification using the 2000 Population Census and the 2006–2024 American Community Surveys from Ruggles et al. (2025). We then plot the returns to schooling of foreign-educated immigrants against GDP per worker in Panel (b) of Figure 5. Again, there are sizable differences in this measure of education quality that are strongly correlated with development. The U.S. labor market rewards each year of schooling from rich countries by ten percent or more, as compared to a return of less than five percent per year of schooling from developing countries. This estimate would be biased by selection only if migrants with different education levels are differentially selected and the extent of differential selection is correlated with development. Schoellman provides several checks to argue that this is not the case, including looking at the wages of refugees.

Finally, Schoellman incorporates these estimates into a measure of human capital. He proposes a human capital production function of the form

$$h_i = \exp\left[\frac{(S_i Q_i)^\eta}{\eta}\right].$$

This functional form has the feature that education quantity and education quality interact in the production of human capital. For example, education quality produces no human capital for workers who do not attend school. He uses this interaction in two ways. First, he estimates the value of the parameter $\eta \approx 0.5$ so that average cross-country educational attainment S_i is an optimal response to education quality Q_i, measured as the returns to schooling of migrants. In this step, he instruments for the returns to schooling using test scores, which provides a third method for scaling test scores. Second, he shows that it is possible to construct quality-adjusted measures of the human capital stock as $\log(h_i) = \frac{0.1 S_i}{\eta}$, where η captures that high educational attainment is associated with higher quality. Here too, quality-adjusted schooling roughly doubles the cross-country variation in human capital relative to years of schooling alone.

Internationally standardized achievement tests focus on primary and secondary education. Testing programs that attempt to evaluate the quality of tertiary education are much rarer and much more limited in scope.[21] Thus, this first body of evidence should really be read as pertaining to primary and secondary schooling. Martellini, Schoellman and Sockin (2024) add to this literature by providing evidence that is specific to the quality of tertiary education. They use the wages of college-educated migrants graduat-

[21] For example, Loyalka et al. (2021) administer tests to computer science and electrical engineering graduates in four countries.

ing from and working in a large number of countries around the world. They estimate a two-way fixed-effects specification where wages are a function of the college the worker attended and the country where they work. Their estimate of college quality is thus the average wages of a college's graduates, adjusted for the country where they work. This measures gross college quality and not college value added, so to some extent it likely reflects the human capital generated during primary and secondary schooling as well.

They estimate college graduate quality for 2,800 colleges worldwide. While some developing countries (notably China and India) have a handful of excellent colleges, many do not. Furthermore, the average quality of college graduates is consistently lower in developing countries. The elasticity of college graduate quality with respect to GDP per worker is roughly in line with the prevailing estimates of (primary and secondary) education quality. Thus, we confirm again that education quality is higher in developed countries and that incorporating this fact substantially increases our estimates of the cross-country variation in human capital stocks.

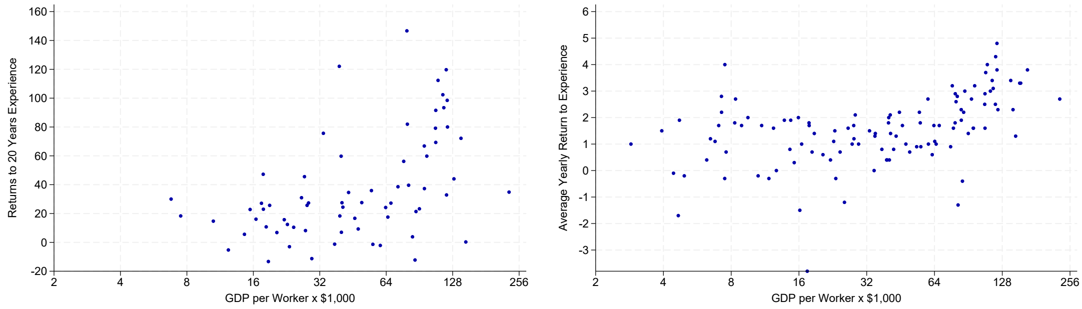
5.2 Experience Human Capital

Mincer (1974) showed that wages vary systematically with both schooling and experience, which is a measure of the years a person could have worked post-graduation (often constructed as age - years of schooling - 6). Early work in the development accounting literature used a macro-Mincer approach to explore whether experience human capital might contribute to cross-country GDP per worker differences (Bils and Klenow, 2000; Klenow and Rodríguez-Clare, 1997; Caselli, 2005). This approach involves valuing each country's stock of experience with an estimate of the return to experience. The common finding is that developing and developed countries have similar levels of experience, which suggests that they have similar levels of experience human capital. This finding reflects two offsetting forces: workers in developing countries are younger, but they spend less time in school.

Recent work revisits this question and finds a very different answer. This revision does not come from changing our estimates of how much experience workers in developing and developed countries have. Rather, researchers have estimated the returns to experience in a careful and systematic way using harmonized data from a wide range of countries and conclude that life-cycle wage growth is slower in developing than in developed countries.[22]

[22] Earlier work relied on estimates of country-level returns to experience collected in the same databases as estimates of returns to education (see footnote 5). These databases did not point to systematic differences in the rate of life-cycle wage growth, likely because these regressions turn out to be sensitive to sample selection and the definition of key variables, which were not standardized in the

Figure 6: Returns to Potential Experience



(a) Immigrants

(b) Non-migrants

Note: Panel (a) reports the return to the first 20 years of origin-country potential experience using estimates from Lagakos et al. (2018*a*) for U.S. immigrants from 65 countries. Panel (b) reports the average annual returns to potential experience among individuals in 115 countries estimated by Jedwab et al. (2023).

Lagakos et al. (2018*b*) first established this result using data from large, representative household surveys from 18 countries from around the world. They estimate the rate at which wages grow over the life cycle, both in the raw data and when controlling for possible confounding factors such as time and cohort effects. Their main finding is that wages roughly double over the life cycle in the most developed countries, but that they increase by only roughly fifty percent in the poorest countries in their sample. In a companion paper, they augment this by estimating the returns to foreign experience among U.S. immigrants from 65 countries from around the world (Lagakos et al., 2018*a*).[23] Panel (a) of Figure 6 plots the estimated wage return to 20–24 years of foreign experience as compared to 0–4 years of foreign experience for each country against that country's PPP GDP per worker. Experience acquired in richer countries is systematically more valued in the U.S. labor market.

Jedwab et al. (2023) add to this finding by estimating returns to experience in a consistent way using the International Income Distribution Database of the World Bank, which consists of harmonized results from 1,500 labor force surveys and censuses from 145 countries around the world. Their database and their estimates also point to higher returns to experience in developed than in developing countries. They report a different statistic, which is the average gain from one additional year of experience. Panel (b) of Figure 6 plots this average return against GDP per worker. Workers in richer countries experience larger wage gains per year of experience.

original studies.

[23] See Coulombe, Grenier and Nadeau (2014) for similar findings among migrants to Canada.

The interpretation of these facts is not obvious, as there are at least three distinct theories of life-cycle wage growth that can be used to think about these cross-country differences: human capital accumulation, search-and-matching frictions, and long-term contracting. The evidence that returns to experience are similar for migrants and non-migrants points towards the view that these differences reflect portable human capital (Lagakos et al., 2018*a*). Lagakos et al. (2018*a*) then consider the implications of these findings for cross-country differences in human capital stocks and for development accounting. They provide bounds that accommodate the two main models of life-cycle human capital. Under the learning-by-doing view, wage growth reflects pure human capital accumulation. Under the Ben-Porath (1967) view, wages also grow because workers endogenously devote a larger share of their time to producing as they age (and a lower share of time to investing) and employers reward them accordingly. Their main finding is that experience human capital also varies across countries by about as much as the human capital generated from years of schooling alone, with the lower bound modestly lower and the upper bound modestly higher.

An important question that remains only partly answered is *why* life-cycle wage growth varies between developing and developed countries. The papers described so far provide some suggestive evidence. For example, Lagakos et al. (2018*b*) show that returns to experience are higher for educated workers and for workers in cognitive occupations. Nonetheless, further work on mechanisms would be useful. The most compelling explanation to date comes from Ma, Nakab and Vidart (2024), who link these differences in life-cycle wage growth to cross-country variation in the extent of training. They document that most training is provided by employers. They also show that workers in developing countries are less likely to receive training than workers in developed countries, both because they are more likely to be self-employed and because they are less than half as likely to receive training even conditional on having an employer. They suggest that this mechanism explains more than half of the differences in life-cycle wage growth. Further work to understand this seemingly important dimension of human capital would be welcome.

5.3 Early Childhood, Parents, and Culture

Moving beyond the influence of Mincer's empirical work, a growing literature documents the lifelong importance of human capital investments made even before school starts (Cunha and Heckman, 2007; Almond and Currie, 2011). This research raises the question of whether there are important cross-country differences in early childhood human capital investment and accumulation.

Unlike for education and experience, the macro-Mincer approach has not yet proved a fruitful avenue for quantifying the importance of early childhood human capital differences. Researchers have developed detailed measurements of investments and human capital formation in early childhood; for example, see Attanasio, Cattan and Meghir (2022) for a recent overview. However, the macro-Mincer approach requires standardized measures across a wide range of countries; currently, none are available. It also requires linking those measures to wages in order to provide an economically meaningful scale. Panel data that link early childhood investments to adult outcomes are rare.

In the absence of such information, the best available evidence on the importance of early childhood human capital and parenting is indirect. Schoellman (2016) estimates the adult wages of Indochinese refugees to the United States as a function of the age at which they arrived in the country. He argues that Indochinese refugees could not control the timing of their arrival in the United States, in which case the coefficient on age at arrival captures the marginal effect of spending an additional year of early childhood in a developing country during difficult times versus the United States. Schoellman estimates that this effect is a fairly precise zero. Since most children migrated as part of families, this result is not informative about the effect of parenting, but rather points out that broader environmental impacts are small or easy to remediate.

Two studies provide useful complementary evidence about the role of parents. Singh (2020) uses student-level panel data from four developing countries to track the evolution of test score differences from ages 5–8. He finds cross-country gaps in test scores already at age 5. Given the lack of preschool facilities in developing countries, this suggests some role for parental or cultural influence in generating differences in learning before children start school.[24]

De Philippis and Rossi (2021) provide direct evidence of parental influence on performance on internationally standardized achievement tests. They leverage the fact that the PISA asks students where they and their parents were born. Second-generation immigrants whose parents were born in a high-test-score country outperform second-generation immigrants whose parents were born in a low-test-score country, even when the two students take the test in the same country or the same school. The estimated parental effect far exceeds what can be accounted for by observable characteristics such as parental education, occupation, or the number of books the parents keep in the house. However, it fades as parents spend more time in their new country (and away from their

[24] He also shows that gaps in learning and test scores grow as students proceed through school. He uses this to estimate what he labels the system-level productivity of the education system: a direct measure of the portion of test score gaps that can be attributed to schooling.

birth country), which suggests that parents may be transmitting cultural influences.

Ek (2024) provides further evidence for an important role for culture in cross-country human capital differences. He studies the labor market performance of immigrants from a wide range of countries to Sweden. His paper makes two main contributions to this discussion. The first is methodological. Unlike other researchers in this area, Ek has access to matched employer-employee data. He uses this to estimate a production function in which workers born in different countries are treated as differentiated labor inputs with distinct productivity levels. An advantage of this production function approach is that he can sidestep several assumptions that are required when interpreting wages, including competitive labor markets and the absence of discrimination. Ek finds large productivity differences between migrants from developing and developed countries, roughly a factor of three even after accounting for observed differences in education and experience.

The second contribution is to ask what factors best predict the variation in worker productivity. Ek uses regressions with a wide variety of country characteristics and argues that cultural factors most strongly and consistently correlate with productivity. In particular, he argues that the cultural value of autonomy (as opposed to obedience or trust) predicts productivity of migrants in Sweden. He provides two additional pieces of evidence to strengthen the argument that this reflects culture. First, he shows that productivity differences partially persist among second-generation immigrants. Second, he provides evidence of sorting on comparative advantage: migrants from countries with high levels of cultural autonomy are more likely to sort into non-routine jobs in Sweden, whereas migrants from countries with high levels of cultural obedience are more likely to sort into routine jobs.

5.4 Health

When Caselli reviewed the state of the literature, the best available evidence on health came from Shastry and Weil (2003) and Weil (2007) (see Weil (2014) for a subsequent overview of the effects of health). These papers repurpose the macro-Mincer approach to quantify the effects of cross-country variation in health. This approach faces two complications. First, we observe only proxies for health, not true health. Second, part of the gain to health comes through higher education. Weil (2007) proposes using height as a widely available and broad measure of health and argues that the direct effect of health on productivity can be estimated using a 3.4 percent return per centimeter of height. Since the richest and poorest countries differ by up to 15 centimeters in average height, health alone can account for a significant portion of cross-country productivity differences.

Perhaps surprisingly, we are aware of no subsequent work that has revisited the measurement of aggregate health stocks or the role of health for development accounting. This likely reflects the fact that it is challenging to measure aggregate health stocks. However, recent work has made progress on this issue (e.g., Hosseini, Kopecky and Zhao, 2026). This area would benefit from further research to either confirm or revise the current state of knowledge.

5.5 Summing Up

Now we sum up the constructive approach – both figuratively and literally. The goal of the constructive approach is to identify the dimensions of human capital that vary across countries, to quantify them, and then to sum them to arrive at an estimate of the total human capital stock by country.

When summing these components, it is important that we avoid double-counting any of them. As an example, consider the interpretation of cross-country differences in test scores. Although we include these gaps prominently in the section on education quality, Singh (2020) and De Philippis and Rossi (2021) both attribute part of these differences to other factors, such as parenting and culture. Similarly, Ek (2024) finds an important role for culture, but this is likely to manifest at least in part through test scores and life-cycle wage growth.

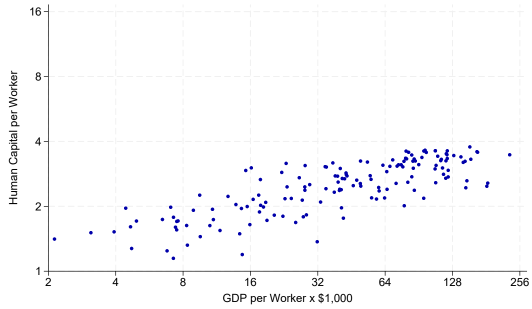
We focus on four measures of human capital accumulation that have a solid evidence base and that are constructed to reduce the risk of double-counting: years of schooling, test scores, experience human capital, and health.[25] Figure 7 shows the raw data for each of these elements. Panel (a) again shows the results for years of schooling alone. Panel (b) shows the results when combining years of schooling and test scores, measured by valuing the HLO test score data at a 20 percent return per standard deviation. This measure of "quality-adjusted schooling" (broadly interpreted) varies by roughly a factor of four, as compared to approximately a factor of three for years of schooling alone.

Panel (c) shows the results for experience human capital, which we estimate by combining the estimates on returns to experience and quantity of experience from Jedwab et al. (2023). The average developed country has more than twice the experience human capital of the average developing country. Panel (d) shows the estimates of health human capital, which we estimate following Weil (2007).[26] Finally, panel (e) shows the

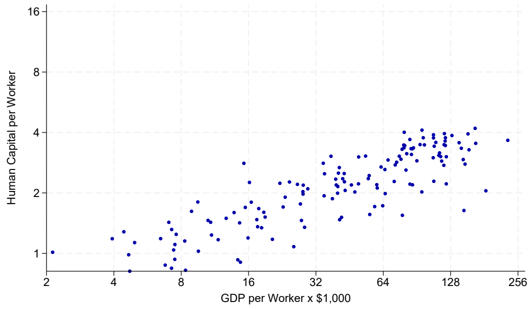
[25] For example, test scores measure performance for a given grade, holding school quantity fixed. Similarly, Weil (2007) constructs the value of health separate from its effect on school attainment.

[26] We take 2019 data on height at age 19 by country and sex from NCD-RisC (2026), which builds

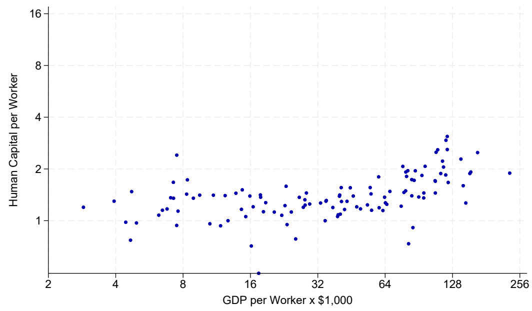
Figure 7: Human Capital Stocks Revisited



(a) Years of schooling

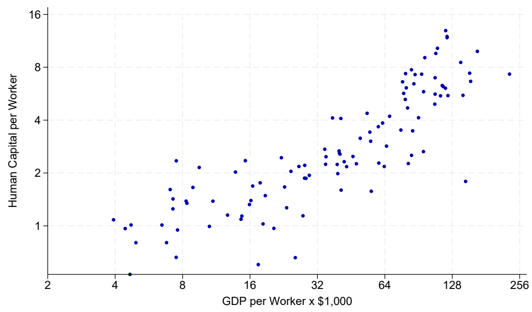


(b) Years + quality (test scores)



(c) Experience (non-migrants)

(d) Health



(e) Total human capital

Note: Panel (a) plots human capital from years of schooling from Barro and Lee (2013) augmented with World Bank (2026), valued at a 10 percent return per year. Panel (b) plots quality-adjusted schooling, which incorporates Harmonized Learning Outcomes from Angrist et al. (2021), valued at 20 percent per standard deviation. Panel (c) plots human capital from experience from Jedwab et al. (2023). Panel (d) plots health based on height at age 19 from NCD-RisC (2020, 2026), converted into human capital following Weil (2007). Panel (e) combines test score-adjusted schooling, experience, and health.

result of combining all these factors at once. Total human capital stocks vary by nearly

on published work in NCD-RisC (2020). We average height across sexes and apply a 3.4 percent return per centimeter.

a factor of 16 and are highly correlated with development.

Table 7 reports the implications of these figures for the role that human capital plays in accounting for cross-country productivity differences. The table follows the same format as Table 2. The first row under each specification shows the results when human capital is equated with years of schooling, which repeats the baseline measures described in Section 2. In this case, human capital accounts for 15–23 percent of cross-country differences. The next two rows show the effect of two different ways of incorporating education quality: using test scores or the approach motivated by returns to schooling of migrants. They lead to a similar conclusion: quality-adjusted schooling accounts for a larger share of GDP per worker differences. The figure is 24 percent under the capital-per-worker specification or 36 percent under the capital-output specification. The next two rows show two ways to account for experience human capital: using non-migrants or migrants. They again point to an important role for experience human capital, in the range of 10–23 percent. Last, we consider the role of health, which we find accounts for 6–10 percent of GDP per worker differences.

The last row under each specification gives one estimate of the total role of human capital. We arrive at this measure of human capital by adding years of schooling, education quality (using test scores), experience (using non-migrants), and health. The results are sizable: by the capital-per-worker specification, human capital now accounts for 43 percent of GDP per worker differences; by the capital-output specification, it accounts for 65 percent. This calculation suggests that a broader measure of human capital has the potential to account for much more of GDP per worker differences. However, we reiterate that there is uncertainty at many key steps in this procedure, both in how to value the various stocks (e.g., what return to test scores to use) and in how to interpret the results (e.g., whether test score differences capture education quality, parenting, or broader cultural influences).

Finally, most of this research focuses on the inputs or investments made in the human capital accumulation process: time spent in school, quality of the school, or training on the job. A natural alternative approach would be to instead measure the *outcome* of these processes: the skills, abilities, and traits that workers possess. This question matters because there is a growing consensus that human capital is multi-dimensional, with distinct roles for physical, cognitive, interpersonal, and decision-making skills, for example (Deming, 2022; Deming and Silliman, 2026). Future research could investigate the scarcity and importance of different skills for cross-country productivity differences.

6 Alternative Approaches to Human Capital

The last section focuses on what we label the constructive approach, which seeks to measure and aggregate the many dimensions of cross-country differences in human capital. In total, a measure that adds education quantity, education quality, experience, and health can account for 60-70 percent of cross-country productivity differences. In this section we consider two alternative approaches. The second approach studies the wage changes of immigrants between developing and developed countries, which are informative about the importance of country versus worker human capital for both wages and output more broadly. The third approach allows workers of different skill levels to be imperfect substitutes, incorporating the canonical model of labor economics into development accounting.

6.1 Deductive Approach

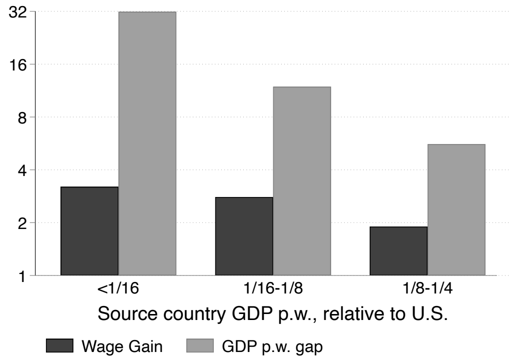
A second approach to measuring human capital leverages the information provided by migrants who work in multiple countries. The intuition behind this approach is that if a migrant supplies the same human capital in both countries, then any change in wages can be attributed to country effects, which capture TFP and physical capital. If this change in wages is sufficiently large, then we infer that TFP and physical capital can account for all of GDP per worker differences. If not, then the remainder is attributed to differences in aggregate human capital between the two countries. The residual nature of this calculation leads us to label this as the deductive approach. It has the advantage of allowing the researcher to quantify the total human capital gap between countries without needing to enumerate or quantify all the possible components of human capital. Despite the very different nature of the exercise, we will see that the results align closely with those of the constructive approach.

The simplest version of the deductive approach rests on the Cobb-Douglas production function (equation (2)) as well as the two assumptions that underpin the macro-Mincer approach, which are that workers with different levels of human capital are perfect substitutes and that labor markets are competitive. The wages for worker j with human capital h_j working in country i can then be expressed as

$$\log(w_{i,j}) = \log\left[(1-\alpha)\left(\frac{K_i}{Y_i}\right)^{\frac{\alpha}{1-\alpha}} A_i\right] + \log(h_j).$$

This expression is the sum of a term that captures country effects (capital-output ratios and TFP) and the worker's human capital. Given data from the same person working

Figure 8: Human Capital, Deductive Approach



Note: Average wage gain at migration and average gap in GDP per worker for migrants to the United States, binned by the gap in productivity between their source country and the U.S. Source: Hendricks and Schoellman (2018).

in a second country i', the first term would change, whereas the second – their portable human capital – would not. Thus, the wage change at migration for someone moving from i to i' is given by

$$\log(w_{i',j}) - \log(w_{i,j}) = \log\left[\left(\frac{K_{i'}}{Y_{i'}}\right)^{\frac{\alpha}{1-\alpha}} A_{i'}\right] - \log\left[\left(\frac{K_i}{Y_i}\right)^{\frac{\alpha}{1-\alpha}} A_i\right].$$

This expression captures the effect of changing country on the worker's wages. Further, the right-hand side captures the differences in two of the key elements needed for development accounting in equation (5). The difference in average human capital between i and i' is then constructed as a residual: it is the difference in GDP per worker that cannot be explained by the difference in capital-output ratios and TFP.

Hendricks and Schoellman (2018) first proposed and implemented this idea using three different data sets that provide information on pre- and post-migration wages of immigrants to the United States. Figure 8 gives the change in wages and difference in GDP per worker for migrants from developing countries in their main data set. The leftmost category shows that migrants from countries with GDP per worker less than 1/16 of the U.S. increased their wages by a factor of 3.2, against an average GDP per worker gap of 31.8. Changing country thus closes $\frac{\log(3.2)}{\log(31.8)} = 34$ percent of the productivity gap for these migrants. The remaining 66 percent then has to be accounted for by human capital gaps. Similar math for the other two groups leads to human capital shares for development accounting of 58 and 63 percent. This implied range of 58–66 percent can be directly compared to the role of human capital judged by the capital-output specification, which we found in the last section to be 65 percent – a strikingly similar number.

A methodological contribution of the deductive approach is that it relaxes the assumption about the selection of migrants used by much of the literature. By comparing wages for the same migrant in two countries, the deductive approach naturally controls for selection on ability of migrants. It also makes it possible to estimate how selected migrants are by comparing their pre-migration wages to representative data sources. Hendricks and Schoellman (2018) find that migrants are positively selected and that the extent of this selection is strongly correlated with development, which confounds some approaches to using the information provided by migrants, including, for example, Hendricks (2002).

It could still be the case that migrants are selected on comparative advantage (e.g., their gains to migration) or that they face frictions to transferring their skills.[27] Using Glassdoor data, Martellini, Schoellman and Sockin (2024) study wage changes at migration for 76,000 skilled migrants moving among 76 countries. They use the fact that they see moves in all directions to provide evidence about this concern. Intuitively, the absence of these complications implies that the wage gains among migrants moving from a developing to a developed country should be exactly equal to the wage losses among migrants who move in the opposite direction. Martellini, Schoellman and Sockin (2024) find deviations from symmetry consistent with selection on comparative advantage or frictions to transferring skills, but they find that adjusting for them has a small effect on the implied accounting results.

6.2 Imperfect Substitutes Approach

So far we have described the constructive and deductive approaches to the measurement of human capital. The third approach differs by allowing for imperfect substitution between unskilled and skilled workers. Doing so integrates the canonical model of labor economics into development accounting and enables a meaningful discussion of the relative supply of and the relative demand for skilled labor. The latter includes, in particular, the skill bias of technology (Acemoglu and Autor, 2011). However, allowing for imperfect substitution also makes inference more complicated, as we now describe.

Consider replacing the standard perfect substitutes labor input $L_i = h_i N_i$ with an

[27] Selection on the wage gains to migration would lead to an upward bias in observed wage gains and a downward bias in the role of human capital for development accounting.

imperfect substitutes aggregator,

$$L_i = \left(z_{u,i} L_{u,i}^{\frac{\sigma-1}{\sigma}} + z_{s,i} L_{s,i}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{11}$$

which posits that total labor input in country i is determined by the unskilled and skilled labor supply $L_{u,i}$ and $L_{s,i}$, aggregated with weights $z_{u,i}$ and $z_{s,i}$ as well as an elasticity of substitution σ that is typically estimated in the labor literature to have a value between 1 and 2. The total supply of labor of each type is in turn the product of the number of workers of each type and the human capital per worker, $L_{u,i} = N_{u,i} h_{u,i}$ and $L_{s,i} = N_{s,i} h_{s,i}$.

Assume that labor markets are competitive, so that the wage per efficiency unit of unskilled labor $w_{u,i}$ and per efficiency unit of skilled labor $w_{s,i}$ are given by their marginal products. Then the observed wage premium ω in country i satisfies

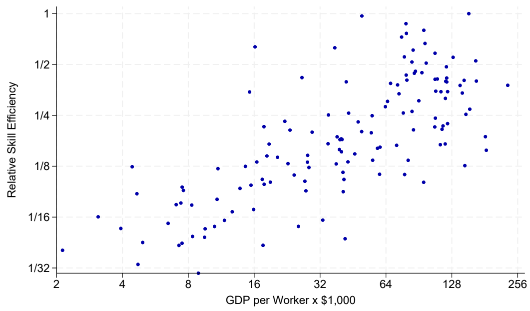
$$\omega_i \equiv \frac{w_{s,i} h_{s,i}}{w_{u,i} h_{u,i}} = \frac{z_{s,i}}{z_{u,i}} \left(\frac{h_{s,i}}{h_{u,i}} \right)^{\frac{\sigma-1}{\sigma}} \left(\frac{N_{s,i}}{N_{u,i}} \right)^{-\frac{1}{\sigma}}. \tag{12}$$

Consider first the case where the skill bias of technology is assumed to be the same in all countries and workers of a given education level are assumed to provide the same human capital in all countries, $z_{s,i}/z_{u,i} = z_s/z_u \forall i$ and $h_{s,i}/h_{u,i} = h_s/h_u \forall i$. In this case, the scarcity of skilled workers in developing countries and the low elasticity of substitution commonly used in the literature imply that developing countries should have vastly higher returns to schooling. This prediction is clearly falsified by the data, which instead suggest that the Mincer return to schooling and the skilled wage premium are roughly constant or slightly decreasing with development (Banerjee and Duflo, 2005; Rossi, 2022).

To be consistent with the data, we need to relax one or both of these assumptions. We can easily compute what Rossi (2022) aptly terms the relative efficiency of skilled labor – the product $\frac{z_{s,i}}{z_{u,i}} \left(\frac{h_{s,i}}{h_{u,i}} \right)^{\frac{\sigma-1}{\sigma}}$ – that rationalizes large differences in the relative supply of skilled labor with small variation in the skill premium. As Caselli and Coleman (2006) already noted, the magnitude of implied variation in this object is large. To give a sense of this, we compute the relative efficiency of skilled labor that is consistent with equation (12) given an approximately constant wage premium and an elasticity of substitution between skill groups of 1.5 (Banerjee and Duflo, 2005; Ciccone and Peri, 2005).[28] We plot this object (normalized so the U.S. is 1) against GDP per worker in Figure 9. The relative efficiency of skilled labor needs to be more than 16 times as large

[28] See Appendix A.2 for measurement details.

Figure 9: Relative Skill Efficiency



Note: This figure plots the relative efficiency of skilled labor for each country against the country's GDP per worker. Relative skill efficiency is computed to satisfy equation (12). See text for details.

in developed countries as in developing countries.

The literature has disagreed about the source of the large variation in the relative efficiency of skilled labor. Caselli and Coleman (2006) attribute it to variation in the skill bias of technology, whereas Jones (2014) attributes it to variation in the relative human capital of skilled labor. As the preceding discussion shows, equation (12) by itself does not contain enough information to discriminate between these two possibilities, which likely explains why the exchange between Caselli and Ciccone (2019) and Jones (2019) fails to find much common ground.

Ultimately, the resolution of this debate comes from incorporating additional information. One approach used in Okoye (2016), Rossi (2022), and Hendricks and Schoellman (2023) is to add the information provided by the returns to schooling of foreign-educated immigrants (Schoellman, 2012). Conceptually, by focusing on returns to schooling in one labor market (the U.S.), the researcher can hold fixed the skill bias of technology $z_{s,U.S.}/z_{u,U.S.}$ and recover the relative human capital of workers from around the world. Returning to equation (12), the relative skill bias of technology is then inferred as the residual that rationalizes why returns to schooling among non-migrants do not vary much with development.

Malmberg (2025) instead uses the information from trade data. He shows that more developed countries export more skill-intensive products. The extent of this revealed comparative advantage is larger than can be rationalized by wages alone. He provides a method to quantify the contribution of skill-biased technology and skill abundance. These two approaches have led to quantitatively similar conclusions: both forces play a role, but the skill bias of technology is quantitatively more important, accounting for 67–91 percent of the variation in the relative efficiency of skilled labor.

These debates matter because the imperfect substitutes labor aggregator has the potential to account for a significant share of cross-country productivity differences. To illustrate this, we make the simplifying assumption that the efficiency of unskilled labor is the same in all countries, $z_{u,i}h_{u,i} \equiv 1$.[29] In this case, we can solve equation (12) for the efficiency of skilled labor in each country as a function of the observed quantity of each type of labor $N_{u,i}$ and $N_{s,i}$ as well as the observed wage premium ω_i. Plugging this into equation (11) yields an expression for each country's labor in terms of observables:

$$L_i = N_{u,i}^{\frac{1}{1-\sigma}} \left(N_{u,i} + \omega_i N_{s,i}\right)^{\frac{\sigma}{\sigma-1}} . \tag{13}$$

We measure $N_{u,i}$ and $N_{s,i}$ in the same manner that we did for Figure 9; we also again approximate ω_i using a 10 percent return per year of schooling in all countries (see Appendix A.2 for details). We compute the labor aggregator for each country for a range of estimates of the elasticity of substitution between skill types. We then use the covariance metric to measure the importance of the "labor aggregator per worker". Table 8 shows the results.

This exercise reveals that incorporating imperfect substitution substantially raises the share of productivity differences accounted for by the labor aggregator. When unskilled and skilled labor are perfect substitutes, the labor aggregator accounts for 19 percent of GDP per worker differences; under the benchmark value of $\sigma = 1.5$, it accounts for a much higher 51 percent. However, as Jones (2014) noted when doing a similar calculation, the results are extremely sensitive to the elasticity of substitution. Jones (2014) argues that the plausible range for this parameter spans $[1, 2]$, while Rossi (2022) focuses on the narrower range $[1.3, 2]$; we compromise by showing results for values in the range $[1.2, 2]$. For values at the low end of this range, the labor aggregator can account for essentially all of productivity differences; at the upper end of the range, it accounts for 35 percent – much smaller than 99 percent, but still twice what the perfect substitutes case implies.

An important note about this calculation is in order. Caselli and Ciccone (2013) show that incorporating imperfect substitution by itself, while holding other factors fixed, *lowers* the role of the labor aggregator. Our approach also computes the efficiency of skilled labor that rationalizes the roughly constant wage premium with development and incorporates this into the calculation. It follows that the labor aggregator really

[29] This assumption is common in the literature and useful for illustration, but it is not innocuous. Jones (2014) discusses evidence that there is heterogeneity in the human capital of unskilled workers $h_{u,i}$ across countries, while Caselli and Coleman (2006) find that $z_{u,i}$ may vary across countries in response to the abundance or scarcity of unskilled labor.

Table 8: Importance of Imperfect Substitutes Labor Aggregator

Factor	share	std. err.	# countries
Capital-per-worker specification			
Aggregator, $\sigma = 1.2$	.659	.057	140
Aggregator, $\sigma = 1.5$	.340	.026	140
Aggregator, $\sigma = 2.0$	.234	.017	140
Capital-output specification			
Aggregator, $\sigma = 1.2$	.987	.085	140
Aggregator, $\sigma = 1.5$	.510	.040	140
Aggregator, $\sigma = 2.0$	.352	.025	140

Note: Table reports the share of cross-country differences in GDP per worker that are accounted for by the imperfect substitutes labor aggregator per worker, $\ell_i = L_i/N_i$, where L_i is given by (13) for various values of σ. Results are based on the covariance metric in (6) applied to the capital-per-worker and capital-output specifications in equations (4) and (5). Source: own calculation using educational attainment data from Barro and Lee (2013) augmented with World Bank (2026); Feenstra, Inklaar and Timmer (2025).

reflects the joint influence of the quantity of skilled labor and the efficiency of skilled labor. Recall that the efficiency of skilled labor in turn reflects large differences in the skill bias of technology along with smaller differences in the quality of skilled labor. In this sense, the "labor aggregator" does not represent labor alone.

Decomposing the underlying contributions of these terms runs into the challenge that the production function is no longer log-additive in the components of interest, so the accounting decompositions are no longer additively separable and order-invariant even under our preferred metric. As emphasized nicely by Caselli and Ciccone (2013), there are then multiple ways to conduct development accounting, each corresponding to a different counterfactual of interest. Our view is that debating how to translate these results into development accounting metrics risks obscuring the main insight, which is that there is a strong, robust correlation among the share of skilled workers, the human capital per skilled worker, and the skill bias of technology in a country. This finding naturally suggests a process of endogenous adjustment or endogenous co-determination. For example, educational choices could be responding to the skill bias of technology as in Restuccia and Vandenbroucke (2013), or the skill bias of technology may be responding to factor endowments as in Acemoglu (2002) and Caselli and Coleman (2006). Further, the results clearly indicate that the joint outcome of this process accounts for a significant share of GDP per worker differences. This appears to be a promising mechanism for future quantitative, equilibrium research in growth and development.

A couple of papers in the literature have contributed to this debate by estimating the cross-country or long-run elasticity of substitution between unskilled and skilled labor. Both Hendricks and Schoellman (2023) and Bils, Kaymak and Wu (2024) argue that the long-run elasticity appears to be higher than conventional estimates, in the range of 4–5. A gap between short-run and long-run elasticities is indicative of additional margins of adjustment that operate over the medium and long-run. One plausible margin of adjustment is precisely the skill bias of technology, which can adjust through appropriate technology adoption or directed technical change. Hendricks and Schoellman (2023) show that standard models of these technology choices are equivalent to allowing for a higher long-run elasticity of substitution, which again points to a process of endogenous adjustment. However, considering and modeling other margins of adjustment may also be useful.

These rich results also suggest that there may be large benefits to exploring other forms of complementarity between human capital and technology. One obvious candidate would be production functions that allow for capital-skill complementarity. Additionally, there is suggestive evidence that technology may interact with other dimensions of human capital besides years of schooling. For example, Lagakos et al. (2018*b*) show that life-cycle wage growth is higher in cognitive occupations, while Deming (2021) shows that it is higher in decision-intensive jobs. Similarly, Ek (2024) argues that the greater focus on non-routine tasks in developed countries may raise the value of autonomy as a cultural trait. These findings again suggest an interaction between technology and human capital accumulation and a process of endogenous co-determination between the two. Further research in this area would be welcome.

7 Other Advances and Open Areas

Our review so far has focused on the canonical elements of development accounting: labor, physical capital, and human capital. In this final section we cover topics that do not fit neatly into these categories. We touch on four areas in which the literature has made useful progress or future research could have a high payoff.

7.1 Capital-Labor Substitutability

Near the end of his review, Caselli (2005) studies deviations from the Cobb-Douglas production function, which gives rise to what he terms non-neutral differences. He finds that these have the potential to be extremely powerful for development accounting. As a key example, he studies the case where capital and labor are aggregated by a CES production function. For values of the elasticity of substitution less than one, the model accounts for a larger share of productivity differences. Further, the results are quantitatively very sensitive to this elasticity: when it is one (Cobb-Douglas), inputs account for a small share of productivity differences, but when it is one-half, inputs account for essentially all of them. He points to the investigation of non-neutral production functions and the elasticity of substitution between capital and labor as useful areas for future research.

The subsequent two decades have seen a great deal of work seeking to estimate this elasticity. In particular, it plays a central role in the recent literature that documents and tries to understand trends in the labor share (Karabarbounis, 2024). Most studies that estimate this elasticity of substitution at the plant or establishment level find values that are less than one. However, standard principles imply that the sectoral and aggregate elasticities of substitution should be larger because they allow for more margins of adjustment (across plants within a sector and across sectors). For example, Oberfield and Raval (2021) find that the elasticity within manufacturing plants is 0.3–0.5, but the elasticity for the manufacturing sector is larger, at 0.5–0.7. The aggregate elasticity is likely to be larger still; some estimates – and some authors – are not ready to rule out that the elasticity might still be larger than one, in which case it would reduce the role of inputs in accounting for cross-country productivity differences (Hubmer, 2023; Karabarbounis, 2024). Further, even if the elasticity is less than one, it makes an important difference whether it is 0.5 or 1. We conclude that we are still not able to quantify this potentially important margin.

7.2 Sectors

A second area highlighted by Caselli was the possibility that cross-country income differences might be particularly large in key sectors. Building on work by Restuccia, Yang and Zhu (2008), he estimated the cross-country gaps in real sector productivity for the agricultural and non-agricultural sectors. The key finding is that gaps were much larger in agriculture than in the rest of the economy. For example, Restuccia, Yang and Zhu (2008) find that the 90-10 ratio of real agricultural output per worker was a factor of 43.5, versus just a factor of 4.5 in non-agriculture. When combined with the observation that most workers in developing countries work in agriculture, this finding raises the possibility that the development puzzle is really an agriculture puzzle. Closely related research pointed to a special role for manufacturing in generating aggregate convergence in productivity and development (Rodrik, 2013, 2016).

This observation kicked off a large literature that investigates the importance of factors such as policies governing land distribution, land rights, and access to modern farm capital for generating agricultural productivity gaps (Adamopoulos and Restuccia, 2014; Adamopoulos et al., 2024; Caunedo and Keller, 2021). Much of this literature uses quantitative equilibrium methods and so falls outside the purview of our survey. However, there are two recent innovations that are within our scope and that have important implications for this research.

One key challenge with early work on sectoral productivity gaps is that the Penn World Table (and other data providers) do not provide sectoral PPPs. Much of this work uses agricultural PPPs published by the Food and Agriculture Organization and uses back-of-the-envelope methods to estimate the PPPs in non-agriculture. In recent work, Boppart et al. (2025) reconstruct non-agricultural PPPs and re-estimate productivity gaps between agriculture and non-agriculture. They find agricultural gaps in line with the previous literature (a 90-10 ratio of 38.5), but much larger cross-country differences in real non-agricultural productivity (a 90-10 ratio of 11.9). This finding suggests that agriculture might be less uniquely unproductive than was previously thought.

Moving forward, an important innovation for work on sectoral productivity gaps is that the Groningen Growth and Development Centre now produces sectoral PPPs and measures of real sectoral output for broad sectors for many countries around the world. These can be found, for example, in their Productivity Level Database and their Economic Transformation Database (Inklaar, Marapin and Gräler, 2026; Kruse et al., 2023). These data are already being used in research studying the evolution of sectoral productivity gaps (Herrendorf, Rogerson and Valentinyi, forthcoming). This is an area where significant progress is likely.

A second important innovation concerns our understanding of sectoral production functions. As discussed in Section 2, the long-run stability of aggregate factor shares is useful evidence in favor of using a Cobb-Douglas production function. However, there is no guarantee that the same stability applies at the sectoral level. Boppart et al. (2025) collect detailed data on prices, inputs, and output for the agricultural sector. They find large, systematic movements that are inconsistent with a Cobb-Douglas production function. In particular, they find that richer countries have lower prices of physical capital, intermediate inputs, and land; higher utilization of the same three inputs per unit of labor; and a lower factor share for labor.[30] This finding implies that part of the large cross-country difference in agricultural productivity can be accounted for by more intensive use of capital, intermediates, and land per worker. As is the case with all development accounting exercises, this should be read as a proximate rather than a

[30]See also Chen (2020) on capital deepening in agriculture.

causal statement. Nonetheless, it points to the need to discard our trusty Cobb-Douglas production function and to develop new model mechanisms for the agricultural sector.

7.3 Firm Productivity

Recent research has made progress in decomposing TFP into the component of productivity that is embedded in firms and the residual portion attributable to the country and its institutions. Two research designs in this area build closely on development accounting ideas and therefore merit discussion here.

First, Bloom, Sadun and Van Reenen (2017) quantify the importance of management for cross-country differences in TFP. Their approach is closely related to the macro-Mincer approach used to quantify cross-country differences in human capital. The authors collect detailed data on management practices for firms in 34 countries. They use their information to construct an aggregate measure of management quality. They then value the effect of management using the results of Bloom et al. (2013), which suggest that a one standard deviation improvement in management raises firm TFP by 10 percent. Combining these two estimates, they find that variation in productivity due to management practices accounts for roughly one-third of the variation in aggregate TFP in their sample, with the share somewhat smaller in the poorest countries for which they have data (e.g., Zambia, Ghana, Mozambique).

Hjort, Malmberg and Schoellman (forthcoming) provide related evidence by looking at the price of high-quality management. They have access to data from two consulting companies that help large firms and multinational firms engage in labor markets for skilled workers in developing and emerging countries. Both data sets show that these firms face high prices for managers and other business professionals in developing countries. For example, the average pay for such workers in the poorest decile of countries in the database is 9.7 times GDP per worker, whereas it is 0.8 times GDP per worker in the richest decile of countries. This finding suggests that there is a scarcity of managers and business professionals in developing countries, which could help explain poor management quality.

Second, Burstein and Monge-Naranjo (2009) and Alviarez, Cravino and Ramondo (2023) both seek to understand how much of aggregate productivity differences stem from differences in firm-embedded productivity. Each leverages an empirical observation that has an analogue in the growth and development literature. Burstein and Monge-Naranjo (2009) study FDI flows, viewing them as flows of firm-embedded productivity from economies where it is abundant to economies where it is scarce. This calculation is closely related to the seminal paper of Lucas (1990), who argues that the lack of capital flows from developed to developing countries is evidence against capital scarcity playing a significant role in GDP per worker differences.

Alviarez, Cravino and Ramondo (2023) leverage cross-country differences in the market shares of multinational firms. Their approach is closely related to the Hendricks and Schoellman (2018) approach of using the wage changes of migrants to disentangle the role of human capital versus country factors. Both empirical patterns point to developed countries having larger stocks of firm-embedded productivity: FDI tends to flow from developed to developing countries, while multinational firms tend to have larger market shares in developing than in developed countries. Although interpreting these findings requires additional model structure, the papers come to similar conclusions: firm-embedded productivity accounts for 28 and 34 percent of cross-country productivity differences when using the capital-output metric outlined in equation (5).

7.4 Accounting for the Distribution of Income

Finally, Gethin (2025) pushes development accounting in a new direction. Whereas all of the results so far seek to quantify the proximate sources of cross-country differences in GDP per worker, he uses development accounting as a tool to understand the proximate sources of differences in the distribution of income. His research incorporates two advances. First, he adopts the imperfect substitutes labor aggregator that we discussed in Section 6.2. This framework allows the wages of unskilled and skilled workers to depend on the interaction of the relative supply of and relative demand for skilled labor, which is the main force he quantifies. Second, he uses detailed microdata on the distribution of educational attainment and wages for a large number of countries around the world.

Gethin uses these data to provide growth accounting results, but much of his approach and many of his insights would naturally carry over to development accounting. In addition to reviewing the implications of his microdata for standard aggregate results, he also provides new results on how the race between the supply of and the demand for skilled labor alters the distribution of wages. His main finding is that rising educational attainment has dampened inequality in most countries and at the global level. This paper suggests new directions in which accounting frameworks and detailed microdata can be used to answer more disaggregated questions going forward.

8 Conclusion

Development accounting offers a simple method for assessing the proximate sources of cross-country productivity differences. Much like decomposing mortality rates into the underlying causes of death, it is a useful diagnostic of which types of explanations might be most promising for further and deeper inquiry. When Caselli (2005) conducted his influential overview of the literature, he came to the conclusion that much of the development puzzle remained a mystery. Differences in the inputs to production accounted for only a modest share of GDP per worker differences, leaving the bulk to be attributed to differences in TFP, the measure of our ignorance. Caselli also offered some potential avenues for improving our understanding, including studying sectoral results and allowing for non-neutral productivity differences.

Our aim has been to review the state of the literature two decades later. The bulk of this article is dedicated to reviewing the advances and improvements made in measuring the factors of production. It is time to take stock: where does all of this work leave us? As we stressed in Section 2, a benefit of covariance metrics is that they are additive. The information contained in Tables 4–8 can then be combined to reach an assessment. We see two main conclusions. First, on the whole, inputs probably account for a larger share of cross-country productivity differences than previously thought. A plausible range spans 45–65 percent, as compared to 28 percent when using the classic setup and the most recent data. The range reflects three findings: hours per worker are higher in developing countries, deepening the puzzle (-0.09); broader measures of human capital account for a substantially larger share (0.6–0.7); and the contribution of physical capital is small and possibly negative (-0.05 to 0.05).

The plausible range of results remains wide, however. Each step of the measurement process relies on data and scaling assumptions that deserve further scrutiny. Further, many important dimensions remain challenging to measure. As two leading examples, we have wide ranges of estimates for the importance of public capital or imperfect substitution across labor types and skill-biased technical change.

We conclude this review with a reminder of the limitations of development accounting. First, development accounting requires external evidence on cross-country differences in production inputs and how to scale the importance of those inputs for production. The set of such factors has expanded since Caselli's review and now includes, for example, firm-embedded productivity. Nonetheless, it remains far from complete, and many interesting and important aspects of growth and development are studied primarily or entirely by methods that fall outside the scope of a review of development accounting.

Second, development accounting only quantifies the proximate sources of cross-country productivity differences. The results covered here suggest the benefits of renewed attention to human capital as a mechanism in the development process, particularly when combined with endogenous skill bias of technology. Likewise, they point to the potential benefits of modeling the agricultural sector using production functions that deviate from Cobb-Douglas. However, this does not help us disentangle complex causal questions. Even if one accepts that human capital varies significantly across countries, development accounting is not useful for sorting out whether this is the result of culture, parenting, schools, or work. Finally, development accounting cannot speak to the deeper causes of cross-country income differences. Our hope is that this review will be a useful guide to promising model features and mechanisms for subsequent work that takes up these issues.

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Online Appendix

A Measurement Details

A.1 Construction of Physical Capital

Researchers used to have to construct estimates of the physical capital stock using raw data on PPP-adjusted investment expenditures by country. The procedure for doing so was as follows. Let τ denote the first year for which investment data are available. Researchers would assign physical capital for this year as $K_{i,\tau} \equiv I_{i,\tau}/(g+\delta)$, where g is the average geometric growth rate of investment over an initial period (typically a decade) and δ is the depreciation rate (typically 6 percent). Physical capital for all subsequent years is then constructed using the perpetual inventory approach

$$K_{i,t+1} = (1-\delta)K_{i,t} + I_{i,t}. \tag{A.1}$$

As noted in the text, an (improved) measure of the capital stock is now available directly from Penn World Table (variable cn).

A.2 Measurement of Unskilled and Skilled Labor

In Section 6.2 we consider the case of an imperfect-substitutes labor aggregator that treats unskilled and skilled labor as distinct inputs. We construct the stocks of each kind of worker using updated data based on Barro and Lee (2013). We define workers as unskilled if they have secondary completed or less education and skilled if they have some tertiary or tertiary complete. Within each category we aggregate workers into "secondary complete equivalents" and "tertiary complete equivalents" under an assumption of perfect substitution, as is standard in the literature. We treat the seven Barro-Lee categories running from no education to tertiary complete as corresponding to 0, 3, 6, 9, 12, 14, and 16 years of schooling. We assume a constant 10 percent rate of return per year of schooling in line with Banerjee and Duflo (2005). Similarly, we approximate the skill premium (the tertiary-secondary wage premium) as $\omega = \exp(0.1 \times 4)$, a constant 10 percent premium for each of the four additional years of schooling.

Rossi (2022) performs similar calculations using actual microdata on workers. This enables him to construct the educational attainment of the working population (as opposed to the adult population age 15–64 in Barro and Lee (2013)). It also enables him to use actual relative wages by educational attainment rather than approximating wages by a constant ten percent return per year of schooling. He finds broadly similar results, suggesting that these approximations do not make a first-order difference for these calculations.

There has also been some debate in the literature about how to define “unskilled” and “skilled” in the development context. Our approach follows Rossi (2022) and the convention in the United States. However, Caselli and Coleman (2006) and Jones (2014) both explore more generous definitions of “skilled” labor that include secondary graduates or even those who have ever attended secondary school. Generally, these alternative definitions amplify the cross-country variation in the supply of skilled labor because by these definitions almost all workers in the United States and many other countries are skilled; see the respective papers for further details.

B Additional Results

B.1 Revisiting Caselli Success Metrics

Table B.1: Success of Factors Revisited: Caselli Metrics

Input bundle	Success 1	Success 2	# countries
Baseline Caselli benchmarks			
Caselli's data	0.39	0.34	94
Latest data (= physical + years)	0.31	0.29	153
Cumulative baseline input bundles			
Physical capital	0.16	0.19	153
Years of schooling	0.04	0.10	153
Years + test-score quality	0.08	0.13	142
Years + quality + experience	0.17	0.18	106
Years + quality + experience + health	0.25	0.24	106
Physical + years + quality	0.43	0.37	142
Physical + years + quality + experience	0.61	0.54	106
Physical + years + quality + experience + health	0.75	0.66	106
Public/private capital extension			
Human + private capital	0.35	0.32	141
Human + private + public capital, $\zeta = 0.10$	0.48	0.44	141
Human + private + public capital, γ_i, $\zeta = 0.10$	0.50	0.47	141
Human + private + public capital, γ_i, $\zeta = 0.20$	0.72	0.67	141
Natural-capital extension			
Human + reproducible capital	0.23	0.31	122
Human + reproducible + natural capital	0.27	0.33	122