Accounting for Cross-Country Income Differences Revisited*

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Abstract

Development accounting is the search for proximate sources of the 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). Recent work has significantly increased our estimates of cross-country variation in human capital stocks. Incorporating this leads to the conclusion that inputs account for 60–73 percent of cross-country income differences, significantly reducing the importance of the residual total factor productivity (TFP) term. New data have also shed light on cross-country productivity differences at the sectoral level. Non-agricultural productivity gaps are now estimated to be larger and closer in magnitude to agricultural productivity gaps. We discuss numerous areas where future research would be beneficial, focusing on the aggregation of different types of investment in physical capital and on measuring sectoral TFP levels.

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1 Introduction

One of the central questions of economics is why output per worker varies so much across countries – the most recent data put the gap between the richest and poorest at a factor of roughly 16, as we show below. 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 proximate sources of cross-country income and productivity differences.

The proximate answers from development accounting can be useful both for guiding deeper investigation and for informing policy decisions. Finding that physical capital accounts for the bulk of income differences would reinforce the use of neoclassical growth models and policies that promote investments in new machinery and equipment. A large role for human capital in development accounting would highlight the value of additional research on why schooling enrollment rates remain so low in poor countries, and how to improve learning in school and skill-building over the life-cycle.

Development accounting is in many respects similar 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 significant mortality gaps are for infectious diseases like malaria and treatable conditions like diarrhea, 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 identify 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) arguably did the most to inspire subsequent research in the field.[1] Hsieh and Klenow (2010) and Caselli (2016) provided updates since then, though recent research has substantially revised these conclusions. This paper synthesizes this research. We focus on areas where new research has substantially changed our understanding of the proximate sources of growth and development or created promising new directions for future investigations.

[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 attributed a much larger explanatory power to total factor productivity.

The main message of Caselli (2005) was that stocks of physical and human capital explained little of the cross-country variation in output per worker. Instead, he attributed most of the variation in development to total-factor productivity (TFP), the residual term taken as exogenous in the exercise. Caselli did not view his conclusion as a success, but rather as a humbling reminder of how much the economics profession still needed to learn, akin to the physics profession's discovery that imperceptible "dark matter" constitutes most of the universe's mass. His findings implied that research on economic growth over-emphasized the neoclassical models of capital accumulation that followed from Solow (1956). It reinforced a broader perception that the literature needed new theories of TFP (Prescott, 1998), and helped spur important quantitative macroeconomic research on such topics as financial frictions, misallocation, and the special role of agriculture.[2]

Most of the progress made since then has focused on improving factor measurement. Improved statistics on working hours deepened the puzzle: workers in poorer countries actually work longer hours, not shorter ones. Progress in measuring physical capital stocks has been made, to be sure, but we conclude that there is no strong case for replacing the standard capital stocks used in the literature. Research has made significant efforts to measure country-specific depreciation rates and natural capital stocks, such as mineral deposits. Yet these additions leave physical capital's explanatory power largely unchanged. Dividing aggregate capital stocks into public and private components holds promise, but there remain unresolved challenges in inferring productive public capital stocks from public expenditure data.

In contrast, human capital per worker has emerged as a much more important factor than previously thought. Better measurements of returns to education and new internationally comparable test scores 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. Cumulatively, measurable stocks of human and physical capital now account for the clear majority of labor productivity differences across countries – 60–73 percent using our preferred metric, or 60–62 percent using Caselli's metric.

The literature also uses new data to estimate the effects of switching countries on

[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.

the wages of migrants. These estimates speak directly to the importance of country-specific factors (physical capital, TFP) versus portable human capital for wages. 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 way to quantify the role of human capital that points in the same direction – quantitatively, human capital accounts for 50–60 percent of cross-country income differences.

The simple Cobb-Douglas aggregate production function has also been confronted with new evidence, and the literature's thinking has evolved significantly there. The emerging consensus favors a production function that combines a Cobb-Douglas function of physical capital and human capital, where human capital itself represents a CES aggregation of high- and low-skilled labor with high substitution elasticity. The sector-neutral TFP term is replaced by separate TFP terms biased toward the high- and low-skilled labor inputs. This approach not only fits the data better but, more importantly, implies an important interaction between skills and skill-biased TFP in accounting for income differences. Richer countries, in other words, are more productive in large part because they have more skilled workers and are better at using those skilled workers.

This revised consensus changes both research priorities and policy lessons. The world turns out to be a great deal more neoclassical than Caselli's article suggested. The field has focused on why developing countries use inputs so unproductively; these results shift attention back to why they lack inputs. Raising average educational attainment must remain an important focus. But the prescription for development ultimately has to be about successfully acquiring and employing new skills in production. Future research should consider more specific measures of skills and their returns in the market, including non-traditional ones, such as entrepreneurial abilities (Queiró, 2022) or decision-making skills (Deming, 2021). More broadly, the ability to operate and manage productive firms and participate effectively in large organizations should become a more central part of this literature.

At the sector level, one of the most enticing angles proposed by Caselli was the divide between the agricultural and non-agricultural sectors, which seemed to hold key clues for understanding development. His calculations, and those by Restuccia, Yang and Zhu (2008), indicated that agriculture was the sector with by far the lowest TFP relative to the rest of the world. Since agriculture employs the largest share of workers in poor countries, explaining agriculture's low productivity was a central part of accounting for aggregate TFP differences. As appealing as this conclusion seemed – and it inspired a lot of subsequent research – it no longer appears quite so promising given better sectoral data on inputs and outputs. As Chen (2020) and Boppart et al. (2025) show, accounting for intermediate inputs carefully is crucial, which points to an agricultural sector production function that is not well approximated by Cobb-Douglas. This implies that agricultural TFP differences are not that much larger than TFP differences in the overall economy.

While reading this review, it is useful to keep in mind two 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. It struggles when either ingredient is absent, as we will find, for example, when we consider the potential importance of public investment. Second, development accounting only quantifies the proximate sources of cross-country income differences. It does not speak to the deep determinants of cross-country income differences and is not useful for discriminating among competing causal mechanisms, as we will discuss, for example, when we touch on the interpretation of cross-country differences in test scores.

Nonetheless, development accounting offers essential insights for researchers and policy makers. It is a valuable complement to quantitative, equilibrium research in growth and development. For example, the finding that cross-country differences in human capital stocks are larger than was previously thought points to the benefits from further examination of theories that emphasize human capital as an important mechanism in generating income differences, even if human capital is not itself the deep cause of those income differences. The finding that education quality and experience vary significantly across countries suggests that policy makers would benefit from thinking beyond maximizing students in seats and instead taking a broader view of education quality and the quality of work experience.

This review is structured as follows. Section 2 develops the basic development accounting exercise in the spirit of Caselli (2005). As described above, development accounting relies on knowledge of the factors of production and the production function. Section 3 describes the progress in measuring the most basic components of the labor input: average hours worked and employment rates. Section 4 focuses on measures of human capital per worker, which is the area with arguably the most progress in the last two decades. Section 5 summarizes work on physical capital stocks and related areas for future research. Finally, Section 6 touches on a number of areas that do not fit neatly into the standard paradigm where progress has been made or is possible. We end with a brief conclusion highlighting areas for future progress.

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 income differences by evaluating their importance using the production function F.

The classic development accounting exercise rapidly 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).[3]

The source 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 Penn World Table (PWT) (Feenstra, Inklaar and Timmer, 2015). Our results use data from PWT 11.0 (Feenstra, Inklaar and Timmer, 2025). Recent versions of the PWT provide multiple measures of GDP; the RGDPo measure (output per

[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. Most recent work specializes to this production function immediately.

worker) 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, undepreciated investment expenditures. Traditionally, researchers would construct this measure themselves using raw data on PPP-adjusted investment expenditures by country. Briefly, 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

$$K_{i,t+1} = (1-\delta)K_{i,t} + I_{i,t}. \tag{3}$$

Recent editions of the PWT include instead 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 that we describe below in Section 5.

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,

$$h_i = \exp(0.1 \times S_i) \tag{4}$$

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]

[4]We augment this with educational attainment data from World Bank (2026) for countries that are missing from Barro-Lee but not 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 schooling for countries with lower levels of schooling, so they incorporated that into their construction of

The output elasticity 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 a factor payment 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. The classic literature follows Gollin (2002), who 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 describe below, using this value instead would have only a modest effect on our preferred estimate. 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 cause. 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 L_i to arrive at

$$y_i = k_i^{\alpha}(A_i h_i)^{1-\alpha}, \tag{5}$$

where we use lower-case variables to denote per worker values. The left-hand side of equation (5) 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 assigns to each factor the corresponding factor share.

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

h. More recent estimates suggest the return to schooling is uncorrelated with average years of schooling or development (Banerjee and Duflo, 2005). 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

$$y_i = \left(\frac{K_i}{Y_i}\right)^{\alpha/(1-\alpha)} h_i A_i. \tag{6}$$

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 (6) 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 the weight put on it.

Caselli (2005) notes that different approaches to development accounting often address different counterfactuals and answer different questions, if sometimes only implicitly. When we use equation (5) to study development accounting, we are asking questions such as, "What would be the effect on cross-country income 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 (5) has one drawback. Varying A or h while holding K/L 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 (6) 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 income differences if all countries had the same TFP, while holding the marginal product of capital and human capital fixed at their current levels?" By incorporating the endogenous adjustment of capital, we are giving greater importance to A and h in the development accounting decomposition.

The second dimension over which papers vary is the metric used to evaluate the relative importance of the factors given either equation (5) or (6). We focus on the

[6]This includes any model where output and input markets are competitive, so that the marginal product of capital is equal to the user cost of capital, and where 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 CRRA preferences.

Klenow and Rodríguez-Clare (1997) metric:

$$\text{share}_x \equiv \frac{\text{cov}(\log(x), \log(y))}{\text{var}(\log(y))}. \tag{7}$$

When evaluating equation (5) the relevant factors are $x \in \left\{k^{\alpha}, h^{1-\alpha}, A^{1-\alpha}\right\}$; when evaluating equation (6), they are instead $x \in \{\left(\frac{K}{Y}\right)^{\alpha/(1-\alpha)}, h, A\}$.[7]

Caselli (2005) focuses on two alternative metrics, which are the ratio of variances $\frac{\text{var}[\log(x)]}{\text{var}[\log(y)]}$ and the 90-10 ratio $\frac{x_{90}/x_{10}}{y_{90}/y_{10}}$. 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 focus on the split of the role accounted for by 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 re-conduct 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 vary and also correlate with output per worker differences. As we will see below, inputs and TFP are both highly correlated with output per worker, so this 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 an updated development accounting using the most recent data. We begin with the most traditional measures of physical

[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. This reflects the view that when trying to understand the development process, each country constitutes an observation.

[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 *success1* measure for that factor that is positive, suggesting that the factor helps account for income differences. The covariance metric would instead yield negative value, rightly indicating that this factor goes in the opposite direction, and is not a promising lead as to what drives income differences.

Table 1: The World Income Distribution: Summary Statistics

	GDP per capita	GDP per worker
10th percentile	2,034	7,596
Median	17,783	42,796
Mean	27,739	58,196
90th percentile	62,890	121,292
log variance	1.40	1.06
90-10 ratio	30.9	16.0

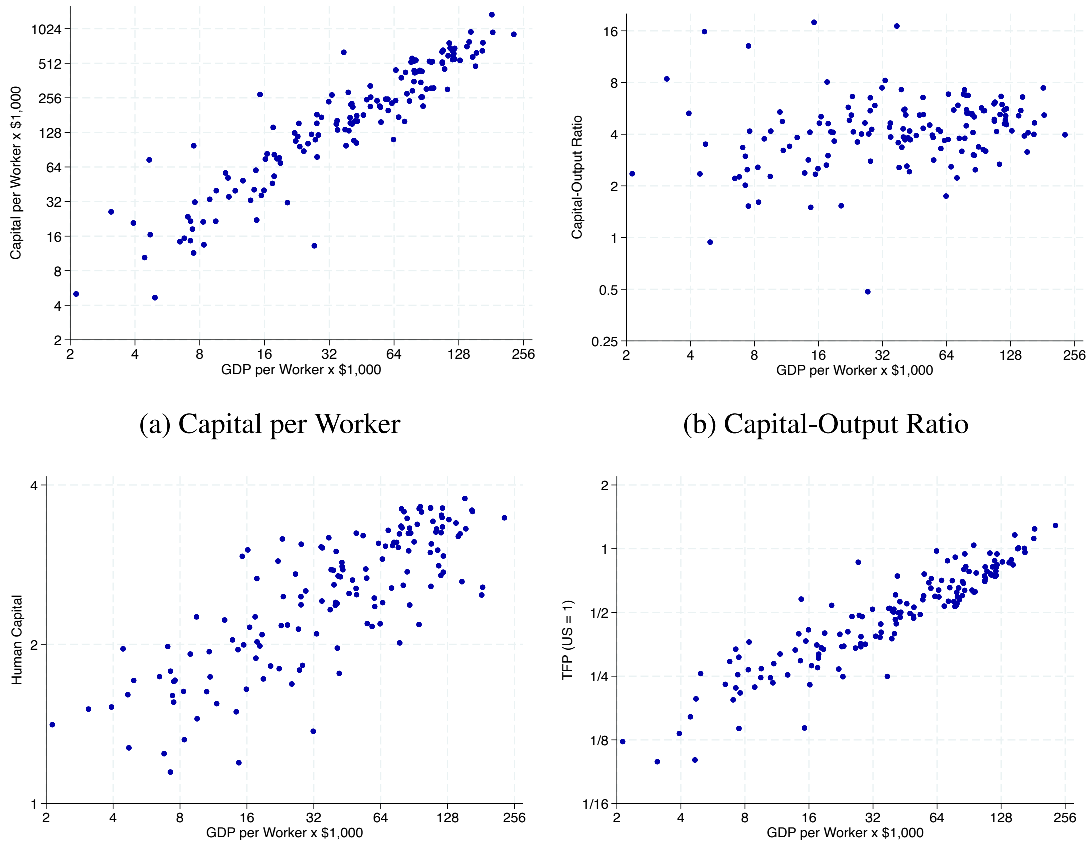
Note: This table reports summary statistics of the world income distribution using GDP per capita and per worker in 2023. GDP is measured in 2021 international dollars. The sample includes 153 countries for which data are available on GDP, physical capital, and years of schooling. Source: Penn World Table 11.0.

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 next poorest country). The remaining countries in total cover 96 percent of the world population and provide extensive coverage of every continent.

These are the productivity differences that we seek to account for. 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 distinct 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 are much more abundant in physical capital when we measure it as the capital-labor ratio. The slope of log capital per worker on log GDP per worker is 1.10, meaning that capital per worker rises even more than one-for-one in aggregate labor productivity. Panel (b) shows that the gap between developed and developing countries is much smaller when we using the capital-output ratio; the slope there is just 0.10. 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 school). It is also increasing in GDP per capita, though less

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: Penn World Table 11.0, Barro-Lee, and the World Bank.

sharply than physical capital, with a slope of 0.22.

Any hope that factors would account neatly for income differences is dispelled in panel (d) of Figure 1, which plots the implied TFP terms. The level of TFP increases robustly in GDP per worker, with a slope coefficient of 0.49. 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 as high. 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

Table 2: Success of Factors, Baseline Measures

Panel A: Klenow-Rodríguez-Clare Covariance Metrics

Factor, x	$share_x$	*std error*	*# 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, $(K/Y)^{\alpha/(1-\alpha)}$	.056	.018	153
Human capital, h	.229	.013	153
Human + physical capital	.284	.024	153

Panel B: Caselli Success Metrics

	$success1$	$success2$	*# countries*
Caselli's data	0.39	0.34	94
Latest data	0.24	0.29	153

Note: Panel A reports the success of factors in accounting for international differences in GDP per worker according to the covariance metrics. Panel B reports the $success1$ and $success2$ measures of Caselli (2005). The first three rows of Panel A cover the capital-per-worker specification in equation (5) and the next three rows cover the capital-output specification of equation (6). The GDP, capital, and employment data come from the Penn World Table version 11.0; the human capital data are constructed from Barro-Lee and World Bank school attainment data and assume a constant 10 percent return to schooling in every country.

results. We start in Panel A with the covariance metric. When we use equation (5) and capital per worker, we find that physical capital accounts for 37 percent of cross-country income differences and human capital for 15 percent. Combined, they account for just over half. However, when we use equation (6) and the capital-output ratio, 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 follows our discussion in the last subsection. The fact that there are large differences in capital-labor ratios but small differences in capital-output ratios between countries points to the fact 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 they are mostly endogenous responses to A. This suggests that only around one-quarter of cross-country income differences can be accounted for by differences in inputs.

An additional benefit of using the capital-output specification is that the results for this case are relatively insensitive to the chosen value of α. The reason is that in this specification, only the capital-output ratio is weighted by a function of α. Further, cross-country differences in the capital-output ratio are anyway small, and so whether we weight them by $\frac{1/3}{2/3} = 0.5$ or $\frac{1/2}{1/2} = 1$ makes little difference. Of course, this is not the case for the capital-per-worker specification.

Panel B revisits the metrics that Caselli prefers in his overview. As we discussed above, they largely lead to the same interpretation. The $success1$ metric shows that the variation in $\log(k^\alpha h^{1-\alpha})$ is small relative to the variation in $\log(y)$; the $success2$ metric shows that the 90-10 ratio in $k^\alpha h^{1-\alpha}$ is small relative to the 90-10 ratio in y. The results are very much in line with our preferred figure of 28 percent from using the covariance metric with the capital-output specification. They are also somewhat lower than what Caselli reported in his overview using data from the 1990s. Thus, using the newest data only confirms the essential message of the literature from its inception: inputs appear to account for a relatively small share of cross-country income differences. 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 yields still 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? A plot of employment-to-population ratios against GDP per worker indeed shows a robust positive relationship: see 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. The higher ratios in richer countries are, however, easily accounted for by the much younger populations of less developed countries. Nearly 40 percent of Sub-Saharan Africans are below the age of 15, for example, compared to just 14 percent in the European Union (United Nations, 2024). Few would argue that insufficient child labor in Africa is a meaningful proximate cause of the continent's underdevelopment.

A more informative metric is the *adult* employment rate. Figure 2, panel (b) plots this statistic (defining adults to be those aged 15 and above) according to the calculations of Bick, Fuchs-Schundeln and Lagakos (2018). Their data show that employment rates are higher on average, 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).

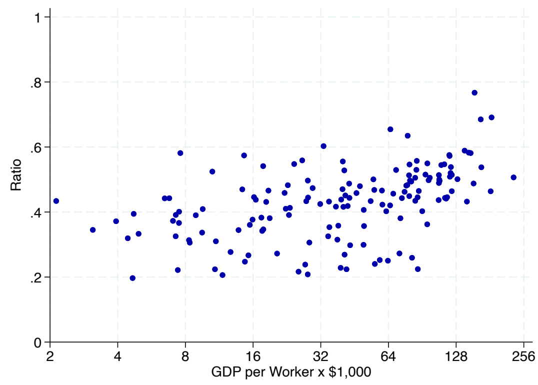
Of course, employment rates can mask significant variation in how many hours adults are working in practice. Since the publication of Caselli's article, many high quality labor force surveys with information on hours of work have become available thanks to the efforts of international organizations like the World Bank and national statistical offices. Panel (c) of Figure 2 plots the average weekly hours worked according to Bick, Fuchs-Schundeln and Lagakos (2018), covering 79 countries in their broadest data set. These data point to higher hours in poorer countries, with the poorest parts of the income distribution working about 50 percent more hours per week than the richest ones. Panel (d) reports the estimates of Gethin and Saez (2025), 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 poor countries working less was not a promising proximate explanation of international income differences. This conclusion – though speculative, given data quality at the time – turned out not to be too far off the current knowledge base. The best measures of labor inputs to date point to employment rates and average hours that are at least as high, and likely higher, in low income countries. This pattern implies that the development puzzle is slightly larger than it initially appears.[9]

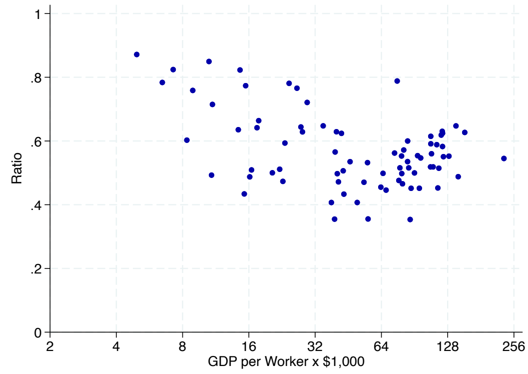
There are limits to focusing solely on the cross-country relationship between the labor input and income per capita, however. Each of the data sets highlighted above points to substantial variation in hours worked between countries at similar levels of

[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.

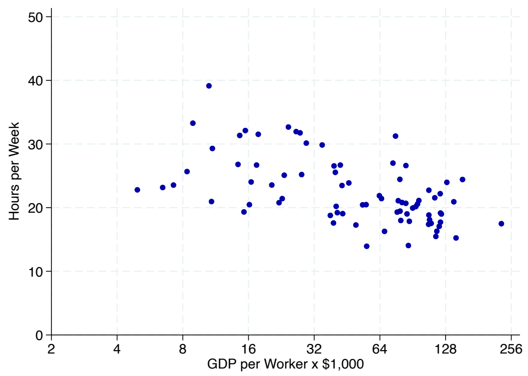
Figure 2: Labor Inputs and Development



(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-Schundeln and Lagakos (2018) and cover 78 countries in various years, most often 2005. Average hours worked per adult in panel (d) come from Gethin and Saez (2025), which covers 139 countries.

development, suggesting that labor inputs can help explain low GDP per worker for 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), and most recently Gethin and Saez (2025)). 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 Measures of Human Capital

New research with better data largely confirms Caselli's conclusion that the quantity of labor was not a major contributor to cross-country income differences. The research on labor quality – human capital – paints a very different picture. Whereas Caselli concluded that it accounted for only a small share of cross-country income differences, recent research has consistently pushed the consensus estimate upwards.[10]

We divide the literature into three pieces. First, many papers seek to quantify additional dimensions of human capital, moving beyond the traditional focus on years of schooling. Second, several papers study the wage changes of cross-country migrants between developing and developed countries, which are informative about the importance of country versus worker human capital for both wages and output more broadly. Third, a growing literature explores the implications of allowing workers of different skills levels to be imperfect substitutes, incorporating the canonical model of labor economics into development accounting.

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

4.1 Constructive Approach

The classic development accounting exercise outlined in Section 2 equates human capital with the value of years of schooling.[11] One strand of the literature expands the measurement of human capital to include other relevant dimensions, such as education quality and experience. 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 income differences, which is useful for both researchers and policy makers. We organize this section by the dimension of human capital considered.

4.1.1 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 test students at a common point in the educational cycle across a wide range of countries. The largest and best-known of these are the OECD's Programme for International Student Assessment (PISA) and the United States Department of Education's Trends in International Mathematics and Science Study (TIMSS), but there are also a number of regional testing programs.

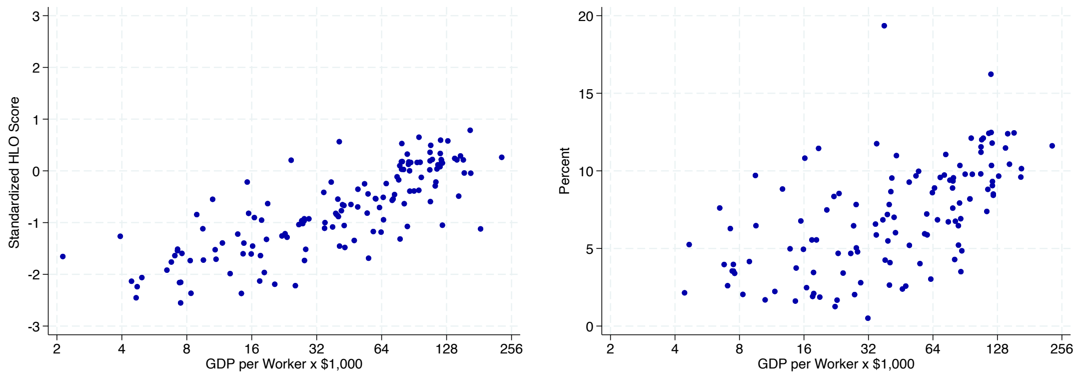
Few developing countries participate in a typical round of PISA or TIMSS. In order to assemble a database covering a large share of the world income distribution, it is necessary to develop a methodology to chain together test scores from different years and testing programs. Angrist et al. (2021) develop 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 countries in total.[12]

These testing programs consistently point to large gaps in test scores between de-

[11] 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 accounted for a small share of cross-country income differences. We discuss below why recent research has revised these conclusions.

[12] 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.

Figure 3: 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.

veloping 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 3. 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 below 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. This leverages the fact that many microeconomic studies evaluate the log-wage returns to both years of schooling and test scores simultaneously. These allow us to construct a measure of human capital that extends equation (4),

$$h_i = \exp(0.1 \times S_i + \rho Q_i), \tag{8}$$

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

The main question is what value of ρ_i to use. Hanushek, Ruhose and Woessmann (2017) review the relevant literature and conclude that the plausible range runs from 9–19 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 to test scores. His approach leverages the fact that the 1995 round of the TIMSS program gave the same test to students in adjacent grades – typically 3rd/4th grade and 8th/9th grade. Intuitively, this allows him to measure education quality as the change in test scores per 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 parameter 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.

Schoellman (2012) proposes an alternative approach that is common in the study of cross-country differences in human capital, which is to leverage the information provided by migrants. A common application studies immigrants from a wide variety of source countries working in a single destination. Intuitively, this approach holds the country-specific factors (such as capital-output ratios and TFP) fixed and allows us to attribute differences in outcomes such as wages to differences in human capital. However, this useful information comes at the cost 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 3. 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 10 percent or more, as compared to less than five percent reward per year of schooling from developing countries. This estimate is only biased by selection if migrants with different education levels are differentially selected and the extent of differential selection is correlated with development. He 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

$$h_i = \exp[(S_i Q_i)^\eta / \eta]. \tag{9}$$

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 the η captures that high educational attainment is associated with higher quality. This approach again leads to the conclusion that quality-adjusted schooling varies by twice as much as years of schooling across countries.

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.[13] 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 graduating from and working in a large number of countries around the world. They estimate a two-way fixed effect 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 measure is a gross measure and not the value added of college, and so to some extent it likely reflects the human capital generated during primary and secondary schooling as

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

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 college graduate quality is consistently lower in developing countries. The elasticity of college graduate quality with respect to GDP per worker is roughly in line with the estimates of (primary and secondary) education quality that prevail in the literature. 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.

4.1.2 Experience Human Capital

Mincer (1974) showed that wages move consistently 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 income 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 suggested that they had similar levels of experience human capital.[14]

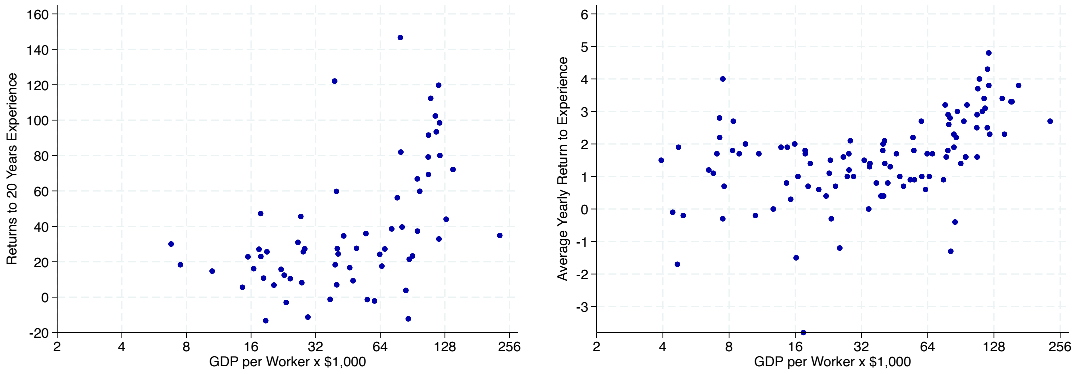
Recent work revisits this question and finds a very different answer. This revision does not come from changing our estimates of how much experience workers in developing and developed countries have. Rather, the literature has estimated the returns to experience in a careful and systematic way using harmonized data from a wide range of countries and come to the conclusion that life-cycle wage growth is slower in developing than in developed countries.[15]

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

[14]This finding reflects two offsetting forces: workers in developing countries are younger, but they spend less time in school.

[15]Earlier work relied on estimates of country-level returns to experience collected in the same databases as estimates of returns to education (see footnote 4). 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 original studies.

Figure 4: 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 U.S. immigrants from 65 countries estimated by Lagakos et al. (2018*a*) Panel (b) reports the average annual returns to potential experience among individuals in 115 countries estimated by Jedwab et al. (2023).

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. Panel (a) of Figure 4 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 estimation also points to higher returns to experience in developed than in developing countries. They report a different statistic, which is the average gain to one year of experience. Panel (b) of Figure 4 plots this average return against GDP per worker. Workers in richer countries experience larger wage gains per year of experience.

The interpretation of these facts is not obvious, as there are at least three distinct theories of life-cycle wage growth which can be used to think about these cross-country differences: human capital accumulation, search and matching, and long-term contracting. The evidence that returns to experience are similar for migrants and non-migrants points towards a view that these differences reflect portable human capital (Lagakos et al., 2018*a*).[16] 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, 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.

4.1.3 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 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 standard-

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

ized 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. Currently, panel data that links 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 to the country. He argues that Indochinese refugees could not control the timing of their arrival to 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.[17]

De Philippis and Rossi (2021) provide direct evidence of the importance of parents for 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 importance of parents far exceeds what can be accounted for by observable characteristics such as parental education, occupation, or the number of books they keep in the house. However, it fades as parents spend more time in their new country (and away from their birth country), which suggests that parents may be carrying a cultural influence that they impart to their children.

Ek (2024) provides further evidence in favor of 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 con-

[17] 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.

tributions 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 where 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 the assumptions that are needed when using wage data, including the potentially concerning assumptions that labor markets are competitive and that migrants do not face 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 to second-generation immigrants. Second, he shows evidence of sorting on comparative advantage: migrants from countries with high levels of cultural autonomy are more likely to sort to non-routine jobs in Sweden, whereas migrants from countries with high levels of cultural obedience are more likely to sort to routine jobs.

4.1.4 Health

When Caselli reviewed the state of the literature, the best available evidence on health came from Shastry and Weil (2003) and Weil (2007). These papers repurpose the macro-Mincer approach to quantify the effects of cross-country variation in health. This approach is complicated by the fact that we observe only (multiple) proxies for health, not true health, but otherwise mirrors the approach taken to measure the effects of schooling. The conclusion from this literature has been that health accounts for a positive but modest share of cross-country income differences.

Perhaps surprisingly, we are aware of no subsequent work that revisits the role of health. This likely reflects the fact that health is challenging to model or measure. However, recent work has made progress on both issues (e.g., Hosseini, Kopecky and Zhao, 2025). This would seem to be an area that would benefit from further research to either confirm or revise the current state of knowledge.

4.1.5 Skills

Most of the research has focused on the inputs or investments made in the human capital accumulation process: time spent in school, quality of the school, learning while working, and parental and cultural influences. A natural alternative approach would be to measure instead the *outcome* of these processes. This approach would ask: what skills, abilities, or traits make workers in developed countries more productive than their counterparts in developing countries? If human capital were truly one-dimensional, then this question would have no practical significance. However, a growing literature documents that human capital is multi-dimensional, with distinct roles for physical, cognitive, interpersonal, and decision-making skills (Deming, 2022; Deming and Silliman, 2026). Incorporating this idea into the measurement of cross-country human capital has the potential to yield additional, richer insights.

The literature to date has made little progress in this direction. A likely culprit is a lack of standardized cross-country data on multi-dimensional skills. One important and notable exception is the OECD Survey of Adult Skills (PIAAC), which tests the literacy, numeracy and problem solving skills of adults in a large number of countries worldwide.[18] Hidalgo-Cabrillana, Kuehn and Lopez-Mayan (2017) leverage this data to construct human capital stocks and perform development accounting exercises, but they still take the scalar human capital view. Bandiera et al. (2025) develop a model of multi-dimensional human capital and use it as a lens to study the PIAAC data. Although they focus on the measurement of misallocation, their framework and data have the necessary elements to quantify the relative abundance of different types of skills.

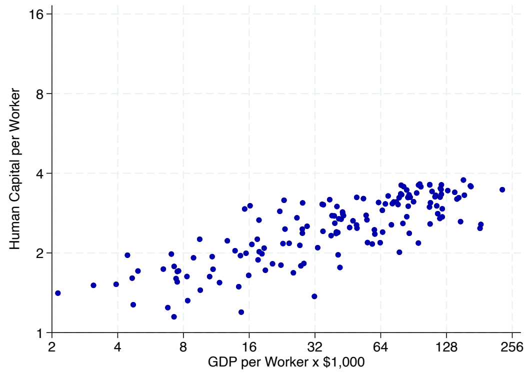
Hjort, Malmberg and Schoellman (forthcoming) provide related evidence by looking at labor prices rather than labor quantities, following somewhat in the spirit of Hsieh (2002). They have access to data from two consulting companies that help large firms and multinational firms engage in labor markets 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, although other interpretations are possible. Further evidence on relative wages of this type would be extremely useful for helping pin down what types of workers are expensive and hence are likely to be scarce.

[18] See also the World Bank STEP Skills Measurement Program (STEP), which extends similar exercises into developing countries.

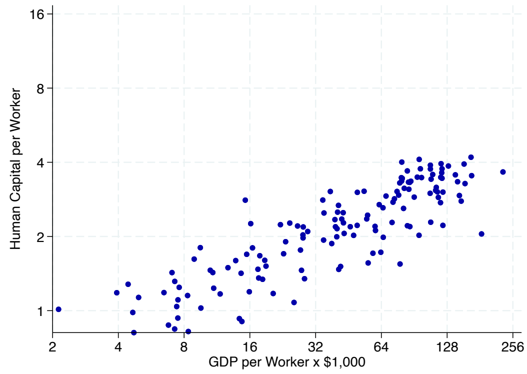
4.1.6 Summing Up

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.

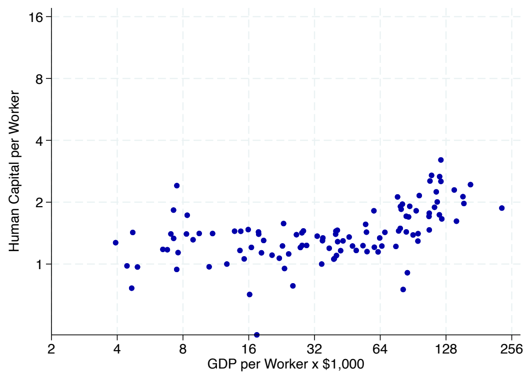
Figure 5: Human Capital Stocks Revisited



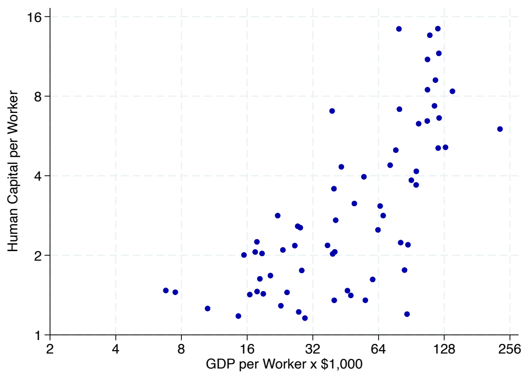
(a) Years of schooling



(b) Years + quality (test scores)



(c) Experience (non-migrants)



(d) Schooling + Experience

Note: Panel (a) plots human capital from years of schooling assuming a common 10 percent returns per year of school. Panel (b) plots human capital from schooling adjusting for quality using test scores. Panel (c) plots human capital from experience using the returns to potential experience estimated by Jedwab et al. (2023) among non-migrants. Panel (d) plots the human capital stocks including schooling, adjusting for quality, plus experience.

When summing these components, it is important that we avoid double-counting any of them. For example, we can include either measures of investments and inputs (schooling, experience, parental inputs) or measures of outcomes (skills, knowledge, abilities), but not both: presumably the return to schooling and experience comes through the accumulation of skills and knowledge, so incorporating both would double count some portion of human capital. Another example comes from 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.

Motivated by the desire to avoid double-counting, we focus on four measures of investments and inputs with a solid base of evidence: years of schooling, test scores, and experience human capital. Figure 5 shows the raw data for each of these elements. Panel (a) shows again 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 rate of 20 percent 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). Developed countries have experience human capital more than twice that of developing countries. Finally, panel (d) shows the result of combining all these factors at once. Total human capital stocks vary by nearly a factor of 16 and are highly correlated with development.

Table 3 reports the implications of these figures for the development accounting results. We start with our preferred case, which is the capital-output specification and covariance metric, shown in the bottom of Panel (a). The first row shows again that years of schooling alone accounts for 23 percent of cross-country income 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, which is that quality-adjusted schooling accounts for 36 percent of cross-country income differences. 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 15–23 percent. Finally, we construct our total measure of human capital, which uses test scores as the source for education quality and non-migrants as the source for experience. We find that the new total human capital stock accounts for 54 percent of cross-country income differences. The last row then adds in the physical capital stock, which leads us to a final estimate: inputs now account for 60 percent of income differences.

The top of Panel (a) uses instead the capital-labor ratio. This specification puts less weight on human capital (now just 36 percent) and more weight on physical capital. But the total for inputs is even larger: 73 percent of cross-country income differences.

Finally, Panel (b) revisits the metrics preferred by Caselli. Again, these metrics point to a much larger role for inputs, which now account for 60–62 percent of cross-country income differences.

4.2 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 cross-country income 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. 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

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

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 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 difference in two of the key elements needed for

Table 3: Success of Factors Revisited

Panel A: Klenow-Rodríguez-Clare Covariance Metrics

Factor, x	$share_x$	$std\ error$	# $countries$
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)	.103	.017	109
Experience (immigrants)	.153	.032	65
Years + quality + experience	.356	.021	106
Human + physical capital	.731	.029	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)	.154	.025	109
Experience (immigrants)	.229	.048	65
Years + quality + experience	.536	.032	106
Human + physical capital	.597	.043	106

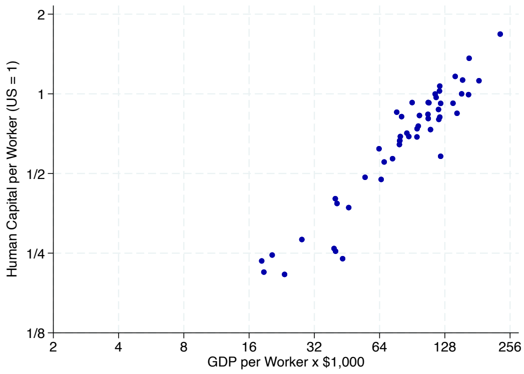
Panel B: Caselli's Success Metrics

	$success1$	$success2$	# $countries$
Caselli's data	0.39	0.34	94
Latest data	0.24	0.29	153
Factors revisited	0.62	0.60	106

Note: Panel A reports the success of each factor according to the covariance metric. Each row corresponds to a different method for measuring factors of production. The data columns report the slope coefficient, standard error, and number of countries in the regression. The first row captures years of schooling assuming a common 10 percent annual return; the second and third rows adjust for schooling quality; the fourth and fifth measure experience human capital; the sixth represents human capital from schooling, adjusting for quality, plus experience. The last row adds human and physical capital. Panel B reports Caselli's success metrics. The first row is for Caselli's data; the second is using the latest data but the basic measures of factors; the bottom row is using the updated measure of human capital, including schooling, adjusting for quality, plus experience.

development accounting in equation (6). The difference in average human capital between i and i' is then constructed as a residual: it is the difference in GDP per worker

Figure 6: Human Capital, Deductive Approach



Note: This figure reports human capital stocks relative to the United States according to the deductive approach. (Source: Martellini, Schoellman, and Sockin (2024))

that cannot be explained by the difference in capital-output ratios and TFP.

Hendricks and Schoellman (2018) first propose and implement this idea using three different data sets that provide information on pre- and post-migration wages of immigrants to the United States. They focus their discussion on immigrants from countries with GDP per worker less than one-quarter of the U.S. level. These migrants roughly triple their (PPP-adjusted) hourly wage when they migrate to the United States. The U.S. is roughly 18 times richer than the average source country for these migrants. This implies that changing country closes 38 percent of the cross-country gap in output per worker. They conclude that the remaining 62 percent can be attributed to gaps in average human capital between the U.S. and this group of developing countries – a number strikingly similar to the 54 percent we derived in the last subsection. Across a wide variety of robustness checks including different income levels and source countries, the relevant range for this share is one-half to two-thirds.

Martellini, Schoellman and Sockin (2024) implement a similar approach using a much larger sample of workers moving among many countries from the database of the website Glassdoor. They estimate and report the information necessary to compute human capital stocks via the deductive approach for 53 countries. We plot these human capital stocks against GDP per worker in Figure 6. They are highly correlated with development and vary substantially between middle-income and rich countries.

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. Martellini, Schoellman and Sockin (2024) use the fact that they observe workers moving among a large set of countries to provide evidence on 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.

4.3 Imperfect Substitution of Labor Types

A third approach to measuring human capital allows 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, which 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 a simple imperfect substitutes labor aggregator,

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

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 1.4 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 unit of skilled labor $w_{s,i}$ are given by their marginal products. Let the average unskilled and skilled worker in country i supply $h_{u,i}$ and $h_{s,i}$ units of the respective type of labor. Then the observed wage premium in country i

satisfies

$$\frac{w_{s,i}h_{s,i}}{w_{u,i}h_{u,i}} = \frac{z_{s,i}}{z_{u,i}} \left(\frac{h_{s,i}}{h_{u,i}}\right)^{\frac{\sigma-1}{\sigma}} \left(\frac{N_{s,i}}{N_{u,i}}\right)^{-\frac{1}{\sigma}}. \tag{10}$$

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).

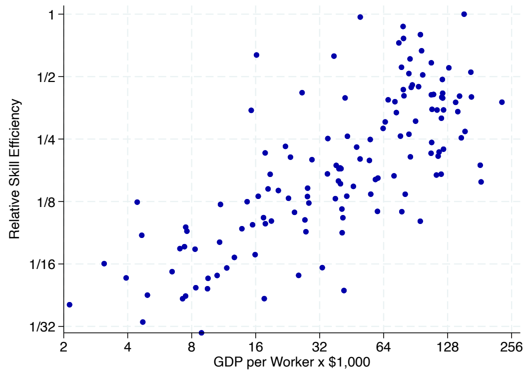
To be consistent with the data, we need to relax one or both of these assumptions. We can easily compute what Rossi (2022) aptly terms the relative efficiency of skilled labor – the product $\frac{z_{s,i}}{z_{u,i}} \left(\frac{h_{s,i}}{h_{u,i}}\right)^{\frac{\sigma-1}{\sigma}}$ – that rationalizes large differences in the relative supply of skilled labor with small variation in the skill premiums. 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 the most recent education data and a constant skill premium.[19] We plot this object (normalized so the U.S. is 1) against GDP per worker in Figure 7. The relative efficiency of skilled labor needs to be more than 16 times larger in developed countries as compared to developing countries.[20]

The literature has disagreed about the source of 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 (10) by itself does not offer the information to discriminate between these two possibilities, which likely explains why the exchange between Caselli and Ciccone (2019) and Jones (2019) fails

[19] We define unskilled workers as those with less than a high school degree and skilled workers as those with a high school degree or more. We convert workers within each group into common units by assuming a ten percent return to each year of schooling. We use $\sigma = 1.4$ to be consistent with Caselli and Coleman (2006). Rossi (2022) performs a similar calculation using microdata on wages and school attainment and finds a broadly similar result for a smaller set of countries.

[20] An alternative resolution is to allow the cross-country or long-run elasticity of substitution to be larger than the conventional estimates. Hendricks and Schoellman (2023) and Bils, Kaymak and Wu (2024) provide evidence that the long-run elasticity is in the range of 4–5. Hendricks and Schoellman (2023) show that allowing for a higher long-run elasticity of substitution is equivalent to modeling an endogenous response of the skill bias of technology to the relative supply of skilled labor.

Figure 7: 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 (10). See text for details.

to find much common ground.[21]

Ultimately, the resolution to 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 (10), 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.

A second approach used in Malmberg (2025) is to use 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 could 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 67–83 percent of the variation in the relative efficiency of skilled labor.

A second debate is how to map these results into statements about the relative importance of human capital and technology for development accounting. The basic model outlined in Section 2 assumes that countries operated a common production function

[21] Interested readers should also see Caselli and Ciccone (2013) and Hendricks and Schoellman (2023) for further insights on this exchange.

that was log-additive in the components of interest. This property allows us to provide accounting decompositions that are additively separable and order-invariant. Once we allow for imperfect substitution between different types of labor and different degrees of skill bias of technology, then no such decomposition exists. 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 important insights that have been gained. The main lesson from this research is that there is a strong, robust correlation between 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 response 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 cross-country income differences. This looks to be a promising mechanism for future quantitative, equilibrium research in growth and development.

It would also be useful to investigate whether a similar process applies to other dimensions of human capital. For example, the value of experience or culturally transmitted traits may interact with a country's technology and its skill bias. This could provide another explanation for why returns to experience are steeper in developed countries. At present, however, we have little direct evidence on the magnitude or importance of these interactions.

5 Measurement of Physical Capital

Research in this literature has also made progress in understanding how the measurement of aggregate physical capital stocks affects the conclusions of development accounting. However, there is still wide-ranging debate about how to measure aggregate capital stocks and whether one should give up on that, opting instead to incorporate multiple capital stocks directly into the production function.[22]

[22]Controversy about how to aggregate different capital types is hardly unique to development accounting, and dates back to the foundational debates in macroeconomics (see Baqaee and Farhi, 2019, and the references therein.).

5.1 Depreciation Rates

Since Caselli's original article, economists connected to the Groningen Growth and Development Center have made steady progress on the core measurement issues at stake in measuring aggregate capital stocks (see e.g. Inklaar and Timmer, 2013; Feenstra, Inklaar and Timmer, 2015; Inklaar, Gallardo Albarrán and Woltjer, 2019). Now, one can easily access aggregate capital stocks at the country-year level through the Penn World Tables. Their painstaking calculations also allow one to relax some of the strong assumptions made by Caselli. Arguably the most questionable such assumption was that there is one single depreciation rate that holds across all countries and years. This assumption plainly flies in the face of the obvious differences in the composition of capital employed in richer and poorer countries. The United States boasts a higher ratio of computers to buildings than Paraguay or Pakistan, for example. Computers expire at a more rapid clip than do buildings. It follows that the United States should not have the same depreciation rate as Paraguay or Pakistan.

Inklaar and Timmer (2013) make progress on this issue by measuring investment separately for six types of capital goods in a wide range of countries, as well as depreciation rates for the same six types of capital goods. The categories they use are structures, transport equipment, computers, communications equipment, software, and other machinery and assets. The composition of capital type varies significantly across countries, and so, in principle, this could lead to significant variation in average depreciation rates. Their resulting estimates imply depreciation rates that are higher in richer countries on average, though with only a very slight (and statistically insignificant) increasing relationship between depreciation rates and GDP per capita. Thus, at least according to their calculations, the conclusions of development accounting are not materially altered by the seemingly extreme (but convenient) assumption of a common world depreciation rate.

Of course, the depreciation rates of Inklaar and Timmer (2013) assumed that each asset type has a common world depreciation rate. This assumption would be violated if computers (or cars, or cell phones) break down more rapidly in less developed countries than in richer ones, due to e.g. inadequate expertise in repairing complex equipment. Graff (2026) provides detailed micro evidence from Uganda suggesting this is indeed the case, implying that actual capital stocks might be significantly smaller in poor countries than currently measured. The opposite pattern may hold true for some capital goods, such as computer software, which could become obsolescent more quickly in richer countries as newer versions arrive on the scene that much faster. 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).[23]

5.2 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 overall that gets siphoned off before the funds can be spent productively. 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 assuming the following law of motion for public capital for each country i:

$$K^G_{i,t+1} = K^G_{i,t}(1 - \delta^G) + \gamma_i I^G_{i,t} \tag{11}$$

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. Caselli did not have separate measures of public and private capital and also did not have estimates of the γ_i terms. This framework thus remains little more than a roadmap for future empirical work.

The reins were taken up since then by researchers at the International Monetary Fund (IMF). Dabla-Norris et al. (2012) 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 proxies indeed pointed to better investment performance in the middle-income countries (like Brazil and South Africa) than the poorer countries in their data (e.g. the Congo). If one takes their index as a direct measure of γ_i, one indeed arrives at significantly smaller capital stocks in lower income countries (Gupta et al., 2014). The challenge is that while higher values of

[23] Inklaar and Timmer (2013) also focused significant attention on the difference in the price of investment goods and consumption goods across countries, and the relatively higher relative price of investment 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 Tables, 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.

their index correspond to better spending practices, the level of the index value does not literally represent the fraction of investment that gets translated into useful capital.

More recently, the IMF has estimated an efficiency term that corresponds more closely to γ_i for 153 countries (see Kapsoli, Mogues and Verdier, 2023, and the references therein). The main methodology underlying their index is a stochastic frontier analysis that focuses on the link between public expenditures (in nominal terms) to specific real outcomes. The real outcomes on which they focus cover 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). In their baseline specification, they estimate an average γ_i value of 0.3 in the poorest countries and 0.5 in the richest ones. They do not plug these estimates back into a development accounting framework, but their estimates point clearly to poorer countries having even lower capital stocks than standard methods suggest.

An alternative consideration related to public and private capital stocks is how they should appear in the production function. Research dating back to Barro (1990) and Baxter and King (1993) treated public and private capital stocks as separate (and complementary) inputs in the production process. One could think of this as production involving separate inputs of sewing machines (provided by the private sector) and paved roads (provided publicly). In principle, one could compute the "aggregate capital stock" by adding the dollar value of sewing machines to the dollar value of roads. But this would be a meaningless number, as only the individual stocks matter for production.

A common such specification of the aggregate production function is:

$$Y_i = (K_i^G)^\zeta (K_i^P)^\alpha (A_i L_i)^{1-\alpha}. \tag{12}$$

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.

In the development accounting literature, Cubas (2020) explored the importance of public capital in this production structure, building his own public and private capital stocks for 90 countries. He did not adjust for the relative efficiency of public investment (i.e. he assumed $\gamma^i = 1$ for all i), to keep the emphasis on the alternative production structure. He inferred the parameter ζ using NIPA data, arriving at a value around 0.1. With this specification, he finds an even larger role for factors of production, as gaps in private capital stocks per capita now appear even larger than previously thought, with more modest cross-country variation in public capital. This significantly increases the explanatory power of capital in accounting for income differences, from 25 percent (according to Caselli's success metric) up to around 40 percent.[24]

A key issue that has held back firm conclusions in this area is the lack of 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 pre-date the credibility revolution in economic (Angrist and Pischke, 2010), and only 7 percent 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 restricting attention to "the area under the lamp-post." The result may well be a significant under-estimate of the marginal product of public capital.[25]

Caselli's original article concluded that the split between public and private capital was "potentially quite important" in helping to account for income differences. Twenty years later, the most natural conclusion is still that this split is "potentially quite important." The case is stronger now though. 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 these, the importance of physical capital stocks in accounting for international income differences should come more sharply into focus.

5.3 Natural Capital

Another area where progress has been made is on 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

[24] 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 income differences but still leaves them larger than when assuming perfect substitution between public and private capital.

[25] Another issue where more research would be valuable is on the degree of complementarity between public and private capital. The Cobb-Douglas specification is chosen for convenience, though an elasticity of substitution around one does not seem implausible. To our knowledge, An, Kangur and Papageorgiou (2019) provide the only estimate of the elasticity of substitution between public and private capital, finding a value around 3.

petroleum, forests, and croplands. Reproducible capital refers to the oil rigs, lumber mills, and tractors that help transform natural resource 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 Tables, 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."

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 to high marginal products. The distinction between natural and reproducible capital is, of course, crucial for this exercise. An investor could decide to deploy a new tractor in Kenya rather than in Iowa, for example, moving her capital from Des Moines to Dar es Salaam. Moving the plains of Iowa over to Kenya would not be quite as easy.

The data on natural capital employed by Caselli and Feyrer (2007) came from the World Bank, which included new estimates of the value of underground resources (including petroleum), forest land, cropland, and pasture land. Urban land is excluded, as is land valuable for touristic purposes, such as beaches or other scenic areas. Despite these and other data limitations, the capital series pointed to considerably larger natural-capital shares in poorer countries on average. The other side of the coin is that reproducible capital shares are considerably larger in richer countries.

Caselli and Feyrer (2007) concluded that the marginal product of reproducible capital was probably not too different across countries, meaning modest potential gains from reallocating capital internationally. The takeaway for development accounting however is that excluding natural capital likely leads to a significant *over-estimate* of the gap in aggregate capital stocks per worker between poor and rich nations. An additional tractor may be roughly equally productive at the margin in Iowa or Kenya, in other words, but by counting only reproducible capital and excluding natural capital, Kenya appears to have less total capital relative to the United States than is actually the case.

In a follow-up study, Monge-Naranjo, Sanchez and Santaeulalia-Llopis (2021) argued that conclusions about global factor misallocation depend crucially on whether the data on natural capital come from rent flows or imputed stocks. They make a persuasive case for the flows data, finding larger global misallocation, especially in past decades. The implication for development accounting remains the same, however: natural capital stocks are a bigger deal in poorer countries, and ignoring them leads to an over-estimate of the capital-per-worker gaps across countries.

Caselli (2016) included both natural and reproducible capital in his "ten years later" paper. The gaps in capital per worker may be smaller than if he had excluded natural capital, but they are still enormous. In the top decile of his data, capital per worker is 150 percent of the U.S. level; in the bottom decile it is 2 percent of the U.S. level. Having 75 times the capital stock per worker is surely going to make workers more productive, and so the conclusion that capital per worker is a major determinant of international income variation still stands.

5.4 Intangibles, and Equipment versus Structures

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.

Another division of the capital stock that has received attention is between equipment and structures. De Long and Summers (1991) used a panel of countries from an early version of the Penn World Tables to document a robust link between GDP growth rates and investment in capital equipment. Investment in structures was not correlated with output growth.

Mutreja (2014) revisited this issue in a development accounting setting, using more recent data series. She finds a cross-sectional pattern that mimics the growth patterns: GDP per capita in levels is strongly correlated with equipment per worker. Structures per worker are correlated too, but not as strongly, with a coefficient on GDP per capita roughly half the size of the equipment coefficient. Assuming a Cobb-Douglas aggregator of equipment and structures, her calculations show a modest reduction in the TFP gaps that are required to explain observed income differences. It is an open question how to aggregate these stocks and whether one should consider a production structure that intertwines different labor and capital types as in Krusell et al. (2000). Recently, Casal and Caunedo (2025) have made recent progress in this area by creating a detailed data set on investment networks linking sectors to the types of capital goods they use for 58 countries across the development spectrum Other work on whether the composition of capital types is less efficient in lower income nations ad if so, why, would be welcome.

6 Other Advances and Open Areas

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

6.1 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 in accounting for cross-country income differences. 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 cross-country income differences. Further, the results are quantitatively very sensitive to this elasticity: when it is one (Cobb-Douglas), inputs account for a small share of income differences, but when it is one-half, inputs account for essentially all of them. He points to 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 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 income 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.

6.2 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 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 the distribution of land and land rights or lack of access to the latest 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 important 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 Tables (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, 2024; Kruse et al., 2022). These data are already being used in research studying the evolution of sectoral productivity gaps (Herrendorf, Rogerson and Valentinyi, 2026). 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. 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 causal statement. Nonetheless, it points to the need to discard our trusty Cobb-Douglas production function and the importance of new model mechanisms when exploring the agricultural sector.

6.3 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 aggregate their information to arrive at an aggregate measure of management quality. They then value the effect of management using the results of Bloom et al. (2013), which suggests 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).

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 with the view that they represent 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 cross-country income differences. Alviarez, Cravino and Ramondo (2023) leverage the data provided by the difference in market shares for a multinational firm that sells in multiple markets. This calculation 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 income differences in the two papers when using the capital-output metric outlined in equation (6).

6.4 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 4.3. This framework allows the wages of unskilled and skilled workers to depend on the relative supply of and relative demand for skilled labor, which is the main force he quantifies. Second, he brings to the table 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.

7 Conclusion

Development accounting offers a simple method for assessing the proximate sources of cross-country income 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 cross-country income differences, leaving the bulk to be attributed to by 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. We review the basic approach and show that using updated data with the classic methods yields similar results as Caselli. We then turn to the recent research, with three main highlights. First, we show that improved measurement has greatly expanded the role for human capital and thus for inputs in accounting for cross-country income differences. Our final number is that inputs now appear to account for 60–73 percent of cross-country income differences. Second, this figure is somewhat complicated by the fact that skill accumulation appears to interact with skill bias of technology in a way that is interesting but makes this statistic less meaningful than the classic decomposition. Third, many of the open areas highlighted by Caselli as profitable areas for future research remain exactly that. Despite new data and substantial work, we have not yet sorted out, for example, how to aggregate public and private capital, or which sectors (if any) make developing countries unproductive.

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 income differences. The results covered here suggest the benefits of renewed attention on 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 on promising model features and mechanisms for subsequent work that takes up these issues.

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