

# The Human Capital Stock: A Generalized Approach\*

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## Abstract

This paper presents a new framework for human capital measurement. The generalized framework can substantially amplify the role of human capital in accounting for cross-country income differences. One natural interpretation emphasizes differences across economies in the acquisition of advanced knowledge by skilled workers.

**Keywords:** human capital, cross-country income differences, ideas, institutions, TFP, division of labor

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# 1 Introduction

This paper considers the measurement of human capital. A generalized framework for human capital accounting is developed in which workers provide differentiated services. Under this framework, human capital variation can play a much bigger role in explaining cross-country income differences than traditional accounting suggests.

To situate this paper, first consider the literature's standard methods and results, which rely on assumptions about (1) the aggregate production function, mapping capital inputs into output, and (2) the measurement of capital inputs. The traditional production function is Cobb-Douglas. In a seminal paper, Mankiw et al. (1992) used average schooling duration to measure human capital and showed its strong correlation with per-capita output (see Figure 1). Overall, Mankiw et al.'s regression analysis found that physical and human capital variation predicted 80% of the income variation across countries.

The interpretation of these regressions is not obvious however, given endogeneity concerns (Klenow and Rodriguez-Clare 1997). To avoid regression's inference challenges, more recent research has emphasized accounting approaches, decomposing output directly into its constituent inputs (see, e.g., the review by Caselli 2005). A key innovation also came in measuring human capital stocks, where an economy's workers were translated into "unskilled worker equivalents", summing up the country's labor supply with workers weighted by their wages relative to the unskilled (Hall and Jones 1999, Klenow and Rodriguez-Clare 1997). This method harnesses the standard competitive market assumption where wages represent marginal products and uses wage returns to inform the productivity gains from human capital investments. With this approach, the variation in human capital across countries appears modest, so that physical and human capital now predict only 30% of the income variation across countries (see, e.g., Caselli 2005) – a quite different conclusion than regression suggested.

This paper reconsiders human capital measurement while maintaining neoclassical assumptions. The analysis continues to use neoclassical mappings between inputs and outputs and continues to assume that inputs are paid their marginal products. The main difference comes through generalizing the human capital aggregator, allowing workers to provide differentiated services.

The primary results and their intuition can be introduced briefly as follows. Write a general human capital aggregator as  $H = G(H_1, H_2, \dots, H_N)$ , where the arguments are the human capital services provided by various subgroups of workers. Denote the standard human capital calculation of *unskilled worker equivalents* as  $\tilde{H}$ . The first result of the paper shows that any human capital aggregator that meets basic neoclassical assumptions can be written in a general manner as (Lemma 1)

$$H = G_1(H_1, H_2, \dots, H_N)\tilde{H}$$

where  $G_1$  is the marginal increase in total (i.e. collective) human capital services from an additional unit of unskilled human capital services. This result is simple, general, and intuitive. It says that, once we have used relative wages in an economy to convert workers into equivalent units of unskilled labor ( $\tilde{H}$ ), we must still consider how the productivity of an unskilled worker depends on the skills of other workers, an effect encapsulated by the term  $G_1$ .

This result clarifies the potential limitations of standard human capital accounting, which focuses on variation in  $\tilde{H}$  across countries. Because the variation in  $\tilde{H}$  is modest in practice, human capital appears to explain very little.<sup>1</sup> In revisiting that conclusion, one possibility is that  $G_1$  varies substantially across countries. Traditional human capital accounting assumes that  $G_1$  is constant, so that unskilled workers' output is a perfect substitute for other workers' outputs. However, this assumption rules out two kinds of effects. First, it rules out the possibility that the marginal product of unskilled workers might be higher when they are scarce ( $G_{11} < 0$ ). Second, it rules out that possibility that the marginal product of unskilled workers might be higher through complementarities with skilled workers ( $G_{1j \neq 1} > 0$ ).<sup>2</sup> In practice, because rich countries are relatively abundant in skilled labor,  $G_1$  will tend to be higher in rich than poor countries, amplifying human capital differences. This reasoning establishes natural conditions under which traditional human capital accounting is downward biased, providing only a lower bound on actual human capital differences across

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<sup>1</sup>For example, comparing the 90th and 10th percentile countries by per-capita income, the ratio of per-capita income is 20 while the ratio of unskilled worker equivalents is only 2 (see, e.g., the review of Caselli 2005).

<sup>2</sup>For example, hospital orderlies might have higher real wages when scarce and when working with doctors. Farmhands may have higher real wages when scarce and when directed by experts on fertilization, crop rotation, seed choice, irrigation, and market timing. Such scarcity and complementarity effects are natural features of neoclassical production theory. They are also found empirically in analyses of the wage structure within countries (see, e.g., the review by Katz and Autor 1999).

countries. This theoretical insight, which draws on general neoclassical assumptions and comes prior to any considerations of data, is a primary result of this paper.

To estimate human capital stocks while incorporating these effects, this paper further introduces a “Generalized Division of Labor” (GDL) human capital aggregator, which features a constant-returns-to-scale aggregation of skilled labor types

$$Z(H_2, H_3, \dots, H_N)$$

that combines with unskilled labor services with constant elasticity of substitution,  $\varepsilon$ . This approach has several useful properties. First, the GDL human capital stock can be calculated without specifying  $Z(\cdot)$ , so that the human capital stock calculation is robust to a wide variety of sub-aggregations of skilled workers. Second, GDL aggregation encompasses traditional human capital accounting as a special case. Third, the human capital stock calculation becomes log-linear in unskilled labor services and unskilled labor equivalents, making it also amenable to linear regression approaches.

Using this aggregator, accounting estimates show that physical and human capital variation can fully explain the wealth and poverty of nations when  $\varepsilon \approx 1.6$ . Meanwhile, regression estimates suggest values for  $\varepsilon$  in a similar range. The capacity for human capital to play a central role in explaining the wealth of poverty of nations appears robustly across various definitions of "skilled" and "unskilled" in the estimation exercises. Moreover, while these calculations are made across countries, existing micro-estimates within countries for related sub-classes of human capital aggregators appear broadly consistent with values of  $\varepsilon$  in this range (e.g., Katz and Autor 1999, Ciccone and Peri 2005, Caselli and Coleman 2006).

The paper closes by considering interpretations. First, the paper considers the "division of labor hypothesis" as a means to explain large human capital differences across countries. While the traditional, perfect-substitutes accounting framework rules out this classic idea about productivity (Smith 1776, Bacon 1620), I discuss how the division of labor provides a natural and empirically relevant candidate explanation for human capital stock differences across countries that is also consistent with skill-biased technical change. Second, the paper considers the meaning of an expanded role for human capital that can more or less eliminate total factor productivity residuals in explaining economic prosperity. Eliminating such residuals can be construed as a central goal of macroeconomic research. At the same

time, because residual productivity differences are often interpreted as variation in "ideas" or "institutions", an elevated role for human capital explanation might be interpreted as limiting these other stories. I will argue, to the contrary, that the embodiment of ideas (facts, theories, methods) into people is a good description of what human capital actually is. Further, this process of human capital investment can be critically influenced by institutions. In this interpretation, the contribution of this paper is not in reducing the roles of ideas or institutions, but in showing how the role of human capital can be substantially amplified, making it a central piece in understanding productivity differences.

Section 2 of this paper develops the generalized framework for calculating human capital stocks. Section 3 considers empirical estimates using both accounting and regression approaches. Section 4 summarizes the results and provides further interpretation. Online Appendices I and II provide numerous supporting analyses as referenced in the text.

**Related Literature** In addition to the literature discussed above, this paper is most closely related to Caselli and Coleman (2006) and Jones (2010). Caselli and Coleman separately estimate residual productivities for high and low skilled workers across countries when allowing for imperfect substitutability between two worker classes. Their estimates continue to use perfect-substitute based reasoning in interpreting a small role for human capital. Jones (2010) provides a model to understand endogenous differences across countries in the quality and quantity of skilled workers and shows that human capital differences expand. These papers will be further discussed below.

## 2 A Generalized Human Capital Stock

Standard neoclassical accounting couples assumptions about aggregation with the assumption that factors are paid their marginal products. Following standard practice, define  $Y$  as value-added output (GDP),  $K_j$  as a physical capital input, and  $H_i = h_i L_i$  as a human capital input, where workers of mass  $L_i$  provide service flow  $h_i$ . The following assumptions will be maintained throughout the paper.

**Assumption 1** (*Aggregation*) *Let there be an aggregate production function*

$$Y = F(K, H, A) \tag{1}$$

where  $H = G(H_1, H_2, \dots, H_N)$  is aggregate human capital,  $K = Q(K_1, K_2, \dots, K_M)$  is aggre-

gate physical capital and  $A$  is a scalar. Let all aggregators be constant returns to scale in their capital inputs and twice-differentiable, increasing, and concave in each input.

**Assumption 2** (*Marginal Products*) Let factors be paid their marginal products. The marginal product of a capital input  $X_j$  is

$$\frac{\partial Y}{\partial X_j} = p_j$$

where  $p_j$  is the price of capital input  $X_j$  and the aggregate price index is taken as numeraire.

The objective of accounting is to compare two economies and assess the relative roles of variation in  $K$ ,  $H$ , and  $A$  in explaining variation in  $Y$ .

## 2.1 Human Capital Measurement: Challenges

The basic challenge in accounting for human capital is as follows. From a production point of view, we would like to measure a type of human capital as an amount of labor,  $L_i$  (e.g., the quantity of college-educated workers), weighted by the flow of services,  $h_i$ , such labor provides, so that  $H_i = h_i L_i$ . The challenge of human capital accounting is that, while we may observe the quantity of each labor type,  $\{L_1, L_2, \dots, L_N\}$ , we do not easily observe their service flows,  $\{h_1, h_2, \dots, h_N\}$ .

The value of the marginal products assumption, Assumption 2, is that we might infer these qualities from something else we observe - namely, the wage vector,  $\{w_1, w_2, \dots, w_N\}$ . The marginal products assumption implies

$$w_i = \frac{\partial F}{\partial H} G_i h_i \quad (2)$$

where  $w_i$  is the wage of labor type  $i$ .<sup>3</sup> It is apparent that the wage alone does not tell us the labor quality,  $h_i$ , but rather also depends on  $(\partial F / \partial H) G_i$ , which is the price of  $H_i$ .<sup>4</sup>

To proceed, one may write the wage ratio

$$\frac{w_i}{w_j} = \frac{G_i h_i}{G_j h_j} \quad (3)$$

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<sup>3</sup>Recall that the wage is the marginal product of labor, not of human capital; i.e.  $w_i = \frac{\partial Y}{\partial L_i}$ . This calculation assumes that we have defined the workers of type  $i$  to provide identical labor services,  $h_i$ . More generally, the same expression will follow if we consider workers of type  $i$  to encompass various subclasses of workers with different capacities. In that case, the interpretation is that  $w_i$  is the mean wage of these workers and  $h_i$  is the mean flow of services ( $H_i/L_i$ ) from these workers.

<sup>4</sup>Other challenges to human capital accounting may emerge if wages do not in fact represent marginal products, which can occur in the presence of market power or through measurement issues; for example, if non-labor activities like training occur over the measured wage interval (see, e.g., Bowlus and Robinson 2011).

which, together with the constant-returns-to-scale property (Assumption 1), allows us to write the human capital aggregate as

$$H = h_1 G \left( L_1, \frac{w_2}{w_1} \frac{G_1}{G_2} L_2, \dots, \frac{w_N}{w_1} \frac{G_1}{G_N} L_N \right) \quad (4)$$

Thus, if wages and labor allocations are observed, one could infer the human capital inputs save for two challenges. First, we do not observe the ratios of marginal products,  $\{G_1/G_2, \dots, G_1/G_N\}$ . Second, we do not know  $h_1$ . To make further progress, additional assumptions are needed. The following analysis first considers the particular assumptions that development accounting makes (often implicitly) to solve these measurement challenges. The analysis will then show how to relax those additional assumptions, providing a generalized approach to human capital accounting that leads to different conclusions.

## 2.2 Traditional Development Accounting

In development accounting, the goal is to compare different countries at a point in time and decompose the sources of income differences into physical capital, human capital, and any residual, total factor productivity. The literature (e.g., see the reviews of Caselli 2005 and Hsieh and Klenow 2010) focuses on Cobb-Douglas aggregation,  $Y = K^\alpha (AH)^{1-\alpha}$ , where  $\alpha$  is the physical capital share of income,  $K$  is a scalar aggregate capital stock, and  $H = G(H_1, H_2, \dots, H_N)$  is a scalar human capital aggregate.

In practice, the labor types  $i = 1, \dots, N$  are grouped according to educational duration in development accounting, with possible additional classifications based on work experience or other worker characteristics. Human capital is then traditionally calculated based on *unskilled labor equivalents*.

**Definition 1** *Define unskilled labor equivalents as  $\tilde{L}_1 = \sum_{i=1}^N \frac{w_i}{w_1} L_i$ , where labor class  $i = 1$  represents the uneducated.*

This calculation translates each worker type into an equivalent mass of unskilled workers, weighting each type by their relative wages. This construct is often referred to as an "efficiency units" or "macro-Mincer" measure, the latter acknowledging that relative wage structures within countries empirically follow a Mincerian log-linear relationship.

Calculations of human capital stocks based exclusively on unskilled labor equivalents can be justified as follows.

**Assumption 3** *Let the human capital aggregator be  $\tilde{H} = \sum_{i=1}^N h_i L_i$ .*

Note that this aggregator assumes an infinite elasticity of substitution between human capital types. This perfect substitutes assumption implies that  $G_i = G_j$  for any two types of human capital. It then follows directly that the human capital aggregate can be written

$$\tilde{H} = h_1 \tilde{L}_1$$

Thus, as a matter of measurement, the perfect substitutes assumption solves the problem that we do not observe the marginal product ratios  $\{G_1/G_2, \dots, G_1/G_N\}$  in the generic aggregator (4) by assuming each ratio is 1.

To solve the additional problem that we do not know  $h_1$ , one must then make some assumption about how the quality of such uneducated workers varies across countries. Let the two countries we wish to compare be denoted by the superscripts  $R$  (for "rich") and  $P$  (for "poor"). One common way to proceed is as follows.

**Assumption 4** *Let  $h_1^R = h_1^P$ .*

This assumption may seem plausible to the extent that the unskilled, who have no education, have the same innate skill in all countries. Under Assumptions 3 and 4, we have

$$\frac{\tilde{H}^R}{\tilde{H}^P} = \frac{\tilde{L}_1^R}{\tilde{L}_1^P}$$

providing one solution to the human capital measurement challenge and allowing comparisons of human capital across countries based on observable wage and labor allocation vectors.

### 2.3 Relaxing the Perfect Substitutes Assumption

To see the implications of Assumption 3 for the conclusions of development accounting, we now return to a generic human capital aggregator  $H = G(H_1, H_2, \dots, H_N)$ .

**Lemma 1** *Under Assumptions 1 and 2, any human capital aggregator can be written  $H = G_1(H_1, H_2, \dots, H_N) \tilde{H}$ .*

All proofs are presented in the appendix.



This result gives us a general, simple statement about the relationship between a broad class of possible human capital aggregators and the "efficiency units" aggregator typically used in the literature. By writing this result as

$$H = G_1 \times h_1 \times \sum_{i=1}^N \frac{w_i}{w_1} L_i$$

we see that human capital can be assessed through three essential objects. First, there is an aggregation across labor types weighted by their relative wages,  $\sum_{i=1}^N \frac{w_i}{w_1} L_i$ , which translates different types of labor into a common type - equivalent units of unskilled labor. Second, there is the quality of the unskilled labor itself,  $h_1$ . Third, there is the marginal product of unskilled labor services,  $G_1$ . The last object,  $G_1$ , may be thought of generically as capturing effects related to the division of labor, where different worker classes produces different services. It incorporates the scarcity of unskilled labor services and complementarities between unskilled and skilled labor services, effects that are eliminated by assumption in the perfect substitutes framework. Therefore, the traditional human capital aggregator  $\tilde{H}$  is not in general equivalent to the human capital stock  $H$ , and the importance of this discrepancy will depend on the extent to which  $G_1$  varies across economies.

**Definition 2** Define  $\Lambda = \left( \frac{H^R/H^P}{\tilde{H}^R/\tilde{H}^P} \right)$  as the ratio of true human capital differences to the traditional calculation of human capital differences.<sup>5</sup>

It follows immediately from Lemma 1 (i.e. only on the basis of Assumptions 1 and 2) that

$$\Lambda = G_1^R/G_1^P$$

indicating the bias induced by the efficiency units approach.

This bias may be substantial. Moreover, there is reason to think that  $\Lambda \geq 1$ ; i.e., that the perfect-substitutes assumption will lead to a systematic understatement of true human capital differences. To see this, note that  $G_1$  is likely to be substantially larger in a rich country than a poor country, for two reasons. First, rich countries have substantially fewer unskilled workers, a scarcity that will tend to drive up the marginal product of unskilled human capital ( $G_{11} < 0$ ). Second, rich countries have substantially more highly educated

<sup>5</sup>Note that, for any production function  $Y = F(K, AH)$ , the term  $AH$  is constant given  $Y$  and  $K$ . Therefore we equivalently have  $\Lambda = (\tilde{A}^R/\tilde{A}^P)/(A^R/A^P)$ , which is the extent total factor productivity differences are overstated across countries.

workers, which will tend to increase the productivity of the unskilled workers to the extent that highly skilled workers have some complementarity with low skilled workers ( $G_{1j \neq 1} > 0$ ). It will follow under fairly mild conditions that  $\Lambda \geq 1$ . One set of conditions is as follows.

**Lemma 2** *Consider the class of human capital aggregators  $H = G(H_1, Z(H_2, \dots, H_N))$  with finite and strictly positive labor services,  $H_1$  and  $Z$ . Under Assumptions 1 and 2,  $\Lambda \geq 1$  iff  $Z^R/H_1^R \geq Z^P/H_1^P$ .*

Thus, under fairly broad conditions, traditional human capital estimation provides only a lower bound on human capital differences across economies. This result, which draws on general neoclassical assumptions and comes prior to any considerations of data, is a primary result of this paper.

### 2.3.1 A Generalized Estimation Strategy

In practice, the extent to which human capital differences may be understated depends on the human capital aggregator employed as an alternative to the efficiency units specification. Here we develop an alternative that (i) can be easily estimated and (ii) nests many approaches, as follows.

**Lemma 3** *Consider the class of human capital aggregators  $H = G(H_1, Z(H_2, \dots, H_N))$ . If such an aggregator can be inverted to write  $Z(H_2, \dots, H_N) = P(H, H_1)$ , then the human capital stock can be estimated solely from information about  $H_1$ ,  $\tilde{H}$ , and production function parameters.*

This result suggests that there may be a broad class of aggregators that are relatively easy to estimate, with the property that the aggregation of skilled labor,  $Z(H_2, H_3, \dots, H_N)$ , need not be measured directly. Moreover, any aggregator that meets the conditions of this Lemma also meets the conditions of Lemma 2. Therefore, in comparison to traditional human capital accounting, any such aggregator allows only greater human capital variation across countries.

A flexible aggregator that satisfies the above conditions is as follows.

**Definition 3** *Define the "Generalized Division of Labor" (GDL) aggregator as*

$$H = \left[ H_1^{\frac{\epsilon-1}{\epsilon}} + Z(H_2, H_3, \dots, H_N)^{\frac{\epsilon-1}{\epsilon}} \right]^{\frac{\epsilon}{\epsilon-1}} \quad (5)$$

where  $\varepsilon \in [0, \infty)$  is the elasticity of substitution between unskilled human capital,  $H_1$ , and an aggregation of all other human capital types,  $Z(H_2, H_3, \dots, H_N)$ .

This aggregator encompasses, as special cases: (i) the traditional efficiency-units aggregator  $\tilde{H} = \sum_{i=1}^N H_i$ , (ii) CES specifications,  $H_\varepsilon = \left( \sum_{i=1}^N H_i^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}}$ , and (iii) the Jones (2010) and Caselli and Coleman (2006) specifications, which assume an efficiency units aggregation for higher skill classes,  $Z = \sum_{i=2}^N H_i$ . More generally, the GDL aggregator encompasses any constant-returns-to-scale aggregation  $Z(H_2, H_3, \dots, H_N)$ . It incorporates conceptually many possible types of labor division and interactions among skilled workers.

By Lemma 3, the aggregator (5) has the remarkably useful property that human capital stocks can be estimated - identically - without specifying the form of  $Z(H_2, H_3, \dots, H_N)$ .

**Corollary 1** *Under Assumptions 1 and 2, any human capital aggregator of the form (5) is equivalently  $H = H_1^{\frac{1}{1-\varepsilon}} \tilde{H}^{\frac{\varepsilon}{\varepsilon-1}}$ .*

Therefore, the calculated human capital stock will be the same regardless of the underlying structure of  $Z(H_2, H_3, \dots, H_N)$ . By meeting the conditions of Lemma 3, we do not need to know the potentially very complicated and difficult to estimate form that this skilled aggregator may take. Related, the understatement of human capital differences across countries is

$$\Lambda_{GDL} = \left( \frac{\tilde{L}_1^R / \tilde{L}_1^P}{L_1^R / L_1^P} \right)^{\frac{1}{\varepsilon-1}} \quad (6)$$

which can be estimated regardless of  $Z(H_2, H_3, \dots, H_N)$ .<sup>6</sup> The findings of the traditional perfect substitutes approach are equivalent to the special case where  $\varepsilon \rightarrow \infty$ .<sup>7</sup> This generalized division of labor approach will be examined empirically in Section 3. We will see that, under reasonable parameterizations, it allows human capital to replace total factor productivity residuals in explaining cross-country income variation.

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<sup>6</sup>From the corollary and the definition of  $\Lambda$ , we have  $\Lambda_{GDL} = \left( \frac{\tilde{H}^R / H_1^R}{\tilde{H}^P / H_1^P} \right)^{\frac{1}{\varepsilon-1}}$ . The term  $\left( \frac{\tilde{H}^R / H_1^R}{\tilde{H}^P / H_1^P} \right)$  is equivalent to the easily measured  $\left( \frac{\tilde{L}_1^R / \tilde{L}_1^P}{L_1^R / L_1^P} \right)$ , because the  $h_1^R$  and  $h_1^P$  terms cancel. Therefore,  $\Lambda_{GDL}$  is invariant to assumptions made regarding  $h_1^R$  and  $h_1^P$ , and, in particular, Assumption 4 is not relevant to this calculation.

<sup>7</sup>Equation (6) also implies that Assumption 3 is a strong version of the traditional accounting framework, which is more generally equivalent to any aggregator written as  $\tilde{H} = H_1 + Z(H_2, H_3, \dots, H_N)$ . In other words, the traditional calculation is correct should unskilled worker services be perfect substitutes for all other worker services.

## 2.4 Relaxing the Identical Unskilled Assumption

In comparing human capital across economies, analyses must also specify the relationship between  $h_1^R$  and  $h_1^P$ . The often implicit assumption is that  $h_1^R = h_1^P$  (Assumption 4), i.e. that the unskilled have the same innate skill in different economies. Alternatively, one might imagine that children in a rich country have initial advantages (including better nutrition and/or other investments prior to starting school) that make  $h_1^R > h_1^P$ .<sup>8</sup> On the other hand, one might be concerned about differences in selection, where those with little schooling are a relatively small part of the population in rich countries. Especially in the presence of compulsory schooling programs, those with little education in rich countries might select on relatively low innate ability, in which case we might imagine  $h_1^R < h_1^P$ . This section considers how to relax Assumption 4 and let data determine  $h_1^R/h_1^P$ .

### 2.4.1 Identifying $h_1^R/h_1^P$

The basic challenge that motivated Assumption 4 is that we do not directly observe  $h_1^R$  or  $h_1^P$ . However, building from the insights of Hendricks (2002), one can make potential headway by noting that immigration allows us to observe unskilled workers from both a rich and poor country in the same economy. Examining immigrants and native-born workers in the rich economy, one may observe the wage ratio

$$\frac{w_1^R}{w_1^{R|P}} = \frac{(\partial F^R/\partial H^R)G_1^R h_1^R}{(\partial F^R/\partial H^R)G_1^R h_1^{R|P}} = \frac{h_1^R}{h_1^{R|P}} \quad (7)$$

where  $w_1^{R|P}$  and  $h_1^{R|P}$  are the wage and skill of immigrants with little education working in the rich country. In other words, immigration allows us to observe workers from different places in the same economy, thus allowing us to eliminate considerations of variation in  $(\partial F/\partial H)G_1$  across countries in trying to infer variation in  $h_1$ .

If we proceed under the assumption that the unskilled immigrants are a representative sample of the unskilled in the poor country, then  $h_1^{R|P} = h_1^P$ . Therefore  $h_1^R/h_1^P = w_1^R/w_1^{R|P}$ , and we can calculate the corrected human capital ratio as

$$\frac{H^R}{H^P} = \frac{G_1^R}{G_1^P} \frac{w_1^R}{w_1^{R|P}} \frac{\tilde{L}_1^R}{\tilde{L}_1^P}$$

Of course, one may imagine that unskilled immigrants might not be representative of the source country's unskilled population. Note that, if immigration selects on higher ability

<sup>8</sup>For example, Manuelli and Sheshadri (2005) makes such arguments.

among the unskilled in the source country, then  $h_1^{R|P} > h_1^P$  and the correction  $w_1^R/w_1^{R|P}$  would then be conservative, providing a lower bound on human capital difference across countries. Hendricks (2002) and Clemens (2011) review the extant literature and conclude that immigrant selection appears too mild to meaningfully affect human capital accounting. The Data Appendix further reviews this literature. In the Data Appendix, I also analyze state-of-the art microdata on Mexican immigration to the United States (Fernandez-Huertas Moraga 2011; Kaestner and Malamud, forthcoming) and confirm modest if any selection from the source population when looking at those with minimal education.<sup>9</sup>

### 3 Empirical Estimation

Given the generalized theoretical results, we reconsider human capital’s role in explaining cross-country income variation. We first consider direct accounting and then consider regression evidence. The analysis uses the flexible, generalized division of labor aggregator (5) and emphasizes comparison with the traditional special case.

#### 3.1 Data and Basic Measures

To facilitate comparison with the existing literature, we use the same data sets and accounting methods in the review of Caselli (2005). Therefore any differences between the following analysis and the traditional conclusions are driven only by human capital aggregation. Data on income per worker and investment are taken from the Penn World Tables v6.1 (Heston et al. 2002) and data on educational attainment is taken from Barro-Lee (2001). The physical capital stock is calculated using the perpetual inventory method following Caselli (2005), and unskilled labor equivalents are calculated using data on the wage return to schooling. In the main analysis, unskilled workers are defined as those with primary or less education. These data methods are further described in the appendix.

Again following the standard literature, we will use Cobb-Douglas aggregation,  $Y = K^\alpha(AH)^{1-\alpha}$  and take the capital share as  $\alpha = 1/3$ . Writing  $Y_{KH} = K^\alpha H^{1-\alpha}$  to account for the component of income explained by measurable factor inputs, Caselli (2005) defines

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<sup>9</sup>See also Jones (2010) for theoretical and empirical analysis of immigrant outcomes among higher skill classes.

the success of a factors-only explanation as

$$success = \frac{Y_{KH}^R / Y_{KH}^P}{Y^R / Y^P}$$

where  $R$  is a "rich" country and  $P$  is a "poor" country. We will denote the success measure for traditional accounting, based on  $\tilde{H}$ , as  $success_T$ .

### 3.2 Accounting Evidence

Table 1 summarizes some basic data. Comparing the richest and poorest countries in the data (the USA and Congo-Kinshasa), the observed ratio of income per-worker is 91. The capital ratio is larger, at 185, but the ratio of unskilled labor equivalents, the traditional measure of human capital differences, appears far more modest, at 1.7. Comparing the 85th to 15th percentile (Israel and Kenya) or the 75th to 25th percentile (S. Korea and India), we again see that the ratio of income and physical capital stocks is much greater than the ratio of unskilled labor equivalents.

Using unskilled labor equivalents to measure human capital stock variation, it follows that  $success_T = 45\%$  comparing Korea and India,  $success_T = 25\%$  comparing Israel and Kenya, and  $success_T = 9\%$  when comparing the USA to the Congo. These calculations suggest that large residual productivity variation is needed to explain the wealth and poverty of nations. These findings rely on unskilled labor equivalents,  $\tilde{L}_1^R / \tilde{L}_1^P$ , to measure human capital stock variation. Because unskilled labor equivalents vary little, human capital appears to add little to explaining productivity differences.<sup>10</sup>

#### 3.2.1 Relaxing the Perfect-Substitutes Assumption

The relationship between the traditional success measure and the success measure for a general human capital aggregator is

$$success = \Lambda^{1-\alpha} \times success_T$$

which follows from Lemma 1 and the definition of  $\Lambda$ .

One can implement a generalized accounting using the GDL aggregator. From (6) and the data in Table 1, it is clear that  $\Lambda_{GDL}$  can be large. While the variation in unskilled labor equivalents,  $\tilde{L}_1^R / \tilde{L}_1^P$ , is modest, the human capital variation that corrects

<sup>10</sup>Figure A1 shows  $success_T$  when comparing all income percentiles from 70/30 (Malaysia/Honduras) to 99/1 (USA-Congo). The average measure of  $success_T$  is 31% over this sample.

for differentiated labor expands according to two objects. One is the relative scarcity of unskilled labor services,  $L_1^R/L_1^P$ . The second is the degree of complementarity between skilled and unskilled labor services, as defined by  $\varepsilon$ .

The literature on the elasticity of substitution between skilled and unskilled labor within countries suggests that  $\varepsilon \in [1, 2]$ , with standard estimates of  $\varepsilon \approx 1.5$ .<sup>11</sup> Table 2 (Panel A) reports the results of development accounting over this range of  $\varepsilon$ , focusing on the Israel-Kenya example. The first row presents the human capital differences,  $H^R/H^P$ , the second row presents the ratio of these differences to the traditional calculation,  $\Lambda_{GDL}$ , and the third row presents the resulting *success* measure for capital inputs in explaining cross-country income differences. As shown in the table, factor-based explanations for income differences are substantially amplified by allowing for labor division. As complementarities across workers increase, the need for TFP residuals decline. For the Israel-Kenya example, the need for residual TFP differences is eliminated at  $\varepsilon = 1.54$ , where human capital differences are  $H^R/H^P = 10.5$ .

One can also consider a broader set of rich-poor comparisons; for example, all country comparisons from the 70/30 income percentile (Malaysia/Honduras) up to the 99/1 percentile (USA/Congo).<sup>12</sup> Calculating the elasticity of substitution,  $\varepsilon$ , at which capital inputs fully explain income differences, shows that the mean value is  $\varepsilon = 1.55$  in this sample with a standard deviation of 0.34. Notably, the estimated values of  $\varepsilon$  typically fall in the same interval as the micro-literature suggests.

### 3.2.2 Relaxing the Identical Unskilled Assumption

Table 2 (Panel B) further relaxes Assumption 4, allowing  $h_1^R/h_1^P$  to be determined from immigration data. Examining immigrants to the U.S. using the year 2000 U.S. Census, the mean wages of employed unskilled workers varies modestly based on the source country (see Figure A2). While the data are noisy, one may infer that mean wages are about 17% lower

<sup>11</sup>See, e.g. reviews in Katz and Autor (1999) and Ciccone and Peri (2005). Most estimates come from regression analyses that may be biased due to the endogeneity of labor supply. Ciccone and Peri (2005) use compulsory schooling laws as a source of plausibly exogenous variation in schooling across U.S. states and conclude that  $\varepsilon \approx 1.5$ . All these estimates consider the elasticity of substitution between high-school and college-educated workers, and they may not extend to primary vs non-primary educated workers. The regression analysis below, however, also suggests  $\varepsilon$  in this range. Online Appendix I provides extensive further analysis using different thresholds between high skill and low skill workers. Those results are summarized below in Section 3.4.

<sup>12</sup>The Malaysia/Honduras income ratio is 3.8. As income ratios (and capital measures) converge towards 1, estimates of  $\varepsilon$  become noisier.

for uneducated workers born in the U.S. compared to immigrants from the very poorest countries, which suggests  $h_1^R/h_1^P \approx .83$  (see Appendix for details).<sup>13</sup>

Such an adjustment lowers the explanatory power of human capital in explaining cross-country variation. The adjustment seems large - it cuts human capital differences by 17%. However, in practice, relaxing Assumption 4 has modest effects compared to relaxing Assumption 3, as seen in Table 2. Now residual TFP differences are eliminated when  $\varepsilon = 1.50$  for the Israel-Kenya comparison. Across the broader set of rich-poor examples, additionally relaxing Assumption 4 leads to a mean value of  $\varepsilon = 1.58$ , with a standard deviation of 0.37.

The human capital stock estimations are summarized for the broader sample in Figure 2. The ratio of human stocks for each pair of countries from the 70/30 income percentile to the 99/1 income percentile is presented. Panel A considers the generalized framework, with  $\varepsilon = 1.6$ . Panel B considers traditional human capital accounting. We see that, as reflected in Table 1, traditional human capital accounting admits very little human capital variation. It appears orders of magnitude less than the variation in physical capital or income. With the generalized framework, human capital differences substantially expand, admitting variation similar in scale to the variation in income and physical capital.

### 3.3 Regression Evidence

Regression analysis in the development accounting context has been the source of debate. While Mankiw, Romer, and Weil (1992) find a large  $R^2$  and theoretically credible relationships between capital aggregates and output, Klenow and Rodriguez-Clare (1997) point out the omitted variable hazards in interpreting such regressions. In practice, because average schooling is highly correlated with income per-capita, regressions of income on schooling variables will tend to show highly significant positive relationships and large  $R^2$ . While this correlation might be causative, it may well not be, and caution is needed.<sup>14</sup>

<sup>13</sup>This micro-data finding stands in contrast to the cross-country analysis of Manuelli and Seshadri (2005), which relies on  $h_1^R \gg h_1^P$ . Manuelli and Seshadri (2005) can be understood as relaxing Assumption 4 but not relaxing Assumption 3, which means that one will require  $h_1^R \gg h_1^P$  to increase the explanatory power of human capital in a cross-country setting. The immigrant wage data is inconsistent with  $h_1^R \gg h_1^P$  unless one assumes that uneducated immigrants to the U.S. select on extremely high ability compared to the non-immigrating population. As discussed in the Data Appendix, there is little evidence to suggest such selection. More generally, Table 2 suggests that much more action comes from relaxing Assumption 3.

<sup>14</sup>An additional challenge for the original Mankiw, Romer, and Weil (1992) approach is the linear use of schooling duration for the human capital aggregator, i.e.  $H = \sum_{i=1}^N s_i L_i$ , where  $s_i$  is the number of years of school. This approach is an efficiency units aggregator (Assumption 3) combined with an additional



Given these concerns, the more telling aspect of regression analysis may come less from high  $R^2$  and more from the implied production function parameters. In particular, while still subject to identification concerns, it is informative to see what regression estimates of production function parameters imply for the accounting. Moreover, to the extent possible, we can see whether parameter estimates are consistent with extant micro-evidence.

Regression can proceed in a straightforward manner using the generalized human capital aggregator. Continuing with the standard Cobb-Douglas production function,  $Y = K^\alpha (AH)^{1-\alpha}$ , define income net of physical capital's contribution as  $\log \hat{Y} = \log Y - \alpha \log K$ . The GDL aggregator implies  $\log \hat{Y} = (1 - \alpha)[\log A + \frac{1}{1-\varepsilon} \log H_1 + \frac{\varepsilon}{\varepsilon-1} \log \tilde{H}]$ . A regression can then estimate

$$\log \hat{Y}^c = \beta_0 + \beta_1 \log H_1^c + \beta_2 \log \tilde{H}^c + u^c \quad (8)$$

where  $c$  indexes countries. The values of  $\varepsilon$  are then implied by the coefficient estimates.<sup>15</sup>

### 3.3.1 Relaxing the Efficiency Units Assumption

Table 3 presents the regression results. Columns (1)-(3) examine (8) while maintaining Assumption 4. Column (1) shows that the explanatory power of  $\log \tilde{H}$  is substantial. The coefficient implies  $\varepsilon = 1.34$ , with a 95% confidence interval of [1.28, 1.34]. Column (2) considers the explanatory power of  $\log H_1$ , which is also substantial. The coefficient implies  $\varepsilon = 1.70$ , with a 95% confidence interval of [1.50, 2.17]. Considering  $\log \tilde{H}$  and  $\log H_1$  together, in column (3), the estimates of  $\varepsilon$  rise somewhat and become noisier, likely due to their colinearity. Notably, to the extent that regression can guide appropriate choices of parameter values, these regression estimates center on values of  $\varepsilon$  that are consistent with very large amplifications of human capital and values of *success*.

### 3.3.2 Relaxing the Identical Unskilled Assumption

Table 3 columns (4)-(6) further examine (8) while additionally relaxing Assumption 4. Immigrant wage outcomes are used to estimate variation in  $h_1^c$  from the U.S. 2000 census, and the measures for  $\log \tilde{H}^c$  and  $\log H_1^c$  are then adjusted accordingly. (The methodology is

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assumption equating skill to years in school, i.e.  $h_i = s_i$ . However, this combination is inconsistent with the wage evidence. Under Assumption 3, the relative skill  $h_i/h_j$  is linear in the relative wage,  $w_i/w_j$ , which is *log-linear* in schooling duration, not linear. Thus the assumption that  $h_i = s_i$  does not appear supportable with a neoclassical aggregator.

<sup>15</sup>Regression estimates that attempt to account for both physical and human capital simultaneously are much noisier, presumably due to the high correlation between these capital stocks and consequent multicollinearity.

further detailed in the Appendix.) In column (4) the coefficient on  $\log \tilde{H}^c$  now implies  $\varepsilon = 1.64$ , with a 95% confidence interval of  $[1.50, 1.87]$ . In column (5) the coefficient on  $\log H_1$  implies  $\varepsilon = 1.88$ , with a 95% confidence interval of  $[1.64, 2.38]$ . Joint estimation again raises the  $\varepsilon$  estimates somewhat and expands the confidence intervals. Overall, these regressions continue to present parameter estimates that are consistent with large amplifications of human capital differences across countries.

### 3.4 Unskilled Workers

The above analysis defines "unskilled" workers as those with completed primary or less schooling and aggregates among unskilled workers assuming they are perfect substitutes for each other. Online Appendix I (Figures A1.1-A1.7 and Table A1.1) extensively explores alternative definitions of the unskilled, including (i) all possible alternative thresholds between skilled and unskilled in the Barro-Lee data and (ii) flexible aggregation among the unskilled themselves, further generalizing the functional form of the human capital aggregator. Using regression estimates to inform parameter values, human capital differences across countries are amplified by a factor of 3.4–7.1, depending on the delineation between skilled and unskilled labor, and the *success* measure ranges from 72%–109%.

A large micro literature predicts  $\varepsilon \approx 1.5$  when delineating the lower skilled group as those with high school or less education (e.g., Katz and Autor 1999, Ciccone and Peri 2005). It may therefore be especially salient that the cross-country regressions in the Appendix estimate  $\varepsilon = 1.5$  using this delineation. With this delineation, regression parameter estimates suggest that human capital differences rise by a factor of 4.7 and the success measure is 88%.

Overall, the amplification of human capital differences appears robust. We see broad consistency between (1) the range of parameter estimates that substantially reduces TFP differences in explicit accounting, (2) regression estimates of these parameters, and (3) available within-country micro-evidence on the substitutability between skilled and unskilled labor. These observations suggest that human capital variation can now play a central role in explaining income variation across countries. These findings are robust to any constant-returns-to-scale specification of the aggregator  $Z(H_2, H_3, \dots, H_N)$ .

### 3.5 Skilled Workers

In allowing for workers to provide differentiated labor services, rather than the same service, the generalized accounting above leads to very different results from the traditional approach. To better understand these results, it is useful to further consider (a) the distinction between wages returns and skill returns when labor is differentiated and (b) the role played by skilled workers.

Recall that in neoclassical theory the wage is a marginal *revenue* product, which is the marginal product (in units of output) times that output's price. Traditional accounting, in assuming perfect substitutes, turns off relative price differences for different workers. Thus, it equates wage returns with skill returns. By contrast, the generalized accounting in this paper adjusts for the implied price effects of intermediate human capital services (see (3)) while otherwise remaining within the neoclassical accounting methodology. In short, we introduce downward sloping demand for different labor services.

To the extent that rich countries "flood the market" with skilled labor and demand is downward sloping, the price of their services will decline. If these skilled workers sustain similar wage returns to schooling as in poor countries, one may then interpret that skilled workers in rich countries provide relatively abundant skilled services (in units of output).<sup>16</sup> In fact, skilled labor supply is far higher in rich countries while wage returns are rather similar across countries. Figure 3 presents these data. Defining  $L_Z$  as the mass of skilled workers and  $w_Z$  as their mean wage, wage return variation is tiny compared to labor supply variation. Taking the Israel-Kenya example, the skilled labor allocation ( $L_Z/L_1$ ) is 2300% greater in Israel, while the wage returns ( $w_z/w_1$ ) are only 20% lower. Taking the USA-Congo example, the skilled labor allocation is 17500% greater in the USA, while wage returns are only 15% lower.

Take these wage returns as given. Then the more downward sloping the demand for skilled services, the greater the *output* returns to schooling in rich countries needed to maintain the *wage* returns to schooling. This provides further intuition for the generalized accounting: As  $\varepsilon$  decreases, demand becomes increasingly downward sloping. Hence lower  $\varepsilon$  leads to larger differences in human capital services across countries (Table 2). Online

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<sup>16</sup>This interpretation requires the elasticity of substitution between skilled and unskilled labor to be greater than one, as is consistent with the evidence. I maintain this assumption in the discussion.

Appendix II provides detailed estimates of the implied skilled services. Taking the Israel-Kenya example, we may infer that skilled workers in rich countries are about 100 times more productive (in units of output) than in poor countries.

One question is whether such large output gains are actually achieved through human capital investment or just happen to be associated with human capital investment. If one accepts instrumental variable estimates where an extra year of schooling raises wages by approximately 10% (see, e.g., the review by Card (2003)), then the schooling investment has a causal interpretation. This follows from the same observation about downward sloping demand in the generalized production function. In rich countries, a 10% gain in wages requires a relatively large increase in output, given the abundant existing supply of skilled labor depressing the relative prices of skilled services. By contrast, in poor countries, a similar wage gain is supported with a much smaller increase in output, given the relative scarcity of skilled workers.<sup>17</sup> Thus if one accepts the micro-literature’s identification of (1) relatively low  $\varepsilon$  and (2) IV estimates of the wage returns from schooling, then advanced schooling in rich countries causes enormous increases in output compared to poor countries.<sup>18</sup>

To be clear, a causative role for human capital does not rule out popular conceptions of skill-biased technological change where, say, skilled workers in rich countries employ relatively advanced ideas or tools. Indeed, while IV wage returns are similar across countries, we can infer highly heterogeneous treatment effects of schooling between rich and poor countries, as discussed above. Understanding why schooling causes such relatively high returns in rich countries poses great avenues for future research – avenues that depart decidedly from the constraints imposed by traditional accounting, which has implied little or no role for human capital. Online Appendix II explores the “division of labor” hypothesis – building out the concept of labor differentiation among skilled workers – which integrates concepts of human capital investment with skill bias in the acquisition of advanced ideas. The concluding section further discusses this interpretation.<sup>19</sup>

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<sup>17</sup>Note that IV estimates of the wage returns to schooling consider both rich and poor countries, as reviewed by Card (2003), and suggest similar wage returns in both settings.

<sup>18</sup>If one does not accept (2), then one would not reach this conclusion (and would more broadly undercut the larger human capital accounting paradigm that infers productivity gains of human capital investments through wage data). Notably, this latter view would not rescue the methodology and conclusions of traditional accounting but rather would reject it on different grounds.

<sup>19</sup>Finally, It is also interesting to consider why the world looks like Figure 3, where wage returns differ little across countries. This behavior is natural when labor supply is endogenous: if wage returns to schooling were unusually high, then more individuals would choose to become skilled, causing the prices of skilled services to fall and constraining wage gains. As discussed in Online Appendix II, simple endogenous labor

## 4 Discussion

### 4.1 Summary

Human capital accounting operates under the assumption that the productivity advantage of human capital (e.g. education, experience) can be inferred by comparing the productivity of those with more human capital with those with less human capital. In practice, this productivity comparison is traditionally made using relative wages: all types of workers in an economy are translated into “unskilled equivalents”, with weights based on the wage gains associated with higher skill (e.g. Klenow and Rodriguez-Clare 1997, Hall and Jones 1999, Caselli 2005). Using this approach to construct human capital stocks, the literature finds that human capital variation across countries is small, explaining little of the differences in per-capita income across countries.

This paper continues within the broad paradigm of human capital accounting, where the productivity advantage of human capital is inferred by comparing workers with more or less human capital. By generalizing the method to a broad class of human capital aggregators, however, the paper reaches three conclusions. First, the productivity gains associated with human capital investments do not reveal themselves through relative wages, unless all workers are perfect substitutes. Second, the perfect substitutes accounting will understate the variation in human capital across countries under broad conditions. Third, a generalized empirical exercise suggests that human capital variation can quite easily explain large income differences across countries. The generalized human capital stock can also be investigated using regression approaches, which suggest production function parameters that are in concert with the micro literature and point to substantially elevated human capital differences. This new accounting thus casts considerable doubt on the findings of the traditional literature.

### 4.2 Interpretations

This paper closes by considering how a larger role for human capital, including one large enough to eliminate TFP differences across countries, may be interpreted. This section first 

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 supply models will drive individuals equilibrium wage returns toward their discount rates (e.g. Willis 1986), as workers optimize their human capital investments, and can act to disconnect equilibrium wage returns from productivity considerations. Endogenous labor supply models may thus help clarify why enormously different skill returns across countries would appear through large differences in labor allocations but little difference in wage returns (Figure 3).

discusses one interpretation – the division of labor hypothesis – and then turns to broader considerations and long-standing debates.

#### 4.2.1 The Division of Labor and Skill Bias

The traditional accounting paradigm, in treating workers as perfect substitutes, not only has large accounting consequences as shown in this paper, but also stands in contrast to old ideas in economics that emphasize the division of labor as a critical source of productivity. Pre-dating even Adam Smith (1776), Francis Bacon’s *Novum Organum* (1620) noted that “...men begin to know their strength when instead of great numbers doing all the same things, one shall take charge of one thing and another of another.” This classic view doesn’t seem controversial when examining modern economies, where workers (especially, skilled workers) bring highly differentiated training and experience to specialized tasks. Consider manufacturing microprocessors, piloting aircraft, performing surgery, adjudicating contracts, or fixing a combine-harvester among many important tasks in advanced economies that require specialized skills. All told, the U.S. Census recognizes over 31,000 different occupational titles.

This paper’s “generalized division of labor” aggregator,  $Z(\cdot)$ , encapsulates productivity gains due to differentiated skills without making narrow claims about specific functional forms. Thus, this paper’s estimates implicitly incorporate the division of labor as a means for driving large productivity differences across countries. On-line Appendix II presents decompositions of skill gains by making further assumptions about  $Z(\cdot)$  and presents a calibration showing how these productivity gains can be mapped into the division of labor. That exercise suggests that enormous skilled-worker productivity differences between Israel and Kenya (the 85-15 percentile country comparison) are consistent with a 4.3-fold increased degree of specialization.<sup>20</sup>

Beyond prima facie evidence for the division of labor in real labor markets, its pedigree in economics, or its potential usefulness in explaining macroeconomic phenomena, the division

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<sup>20</sup>In a companion paper (Jones 2010), I consider micro-mechanisms that can obstruct collective specialization. The model shows how poor economies can emerge as places where skilled workers do relatively similar things, to paraphrase Bacon, and shows how differences in the division of labor may explain several stylized facts about the world economy. As one piece of prima facie evidence, consider that Uganda has 10 accredited medical specialties while the U.S. has 145 accredited medical specialties. Or consider that MIT offers 119 courses across 8 sub-specialties within aeronautical engineering alone, while Uganda’s Makerere University, often rated as the top university in Sub-Saharan Africa outside South Africa, offers no specialized aeronautics courses within its engineering curriculum.

of labor can make a potentially stronger claim upon the development process. Namely, if we believe that productive ideas are too many for one person to know, then the division of labor becomes necessary to achieve advanced productivity. This logic follows to the extent that an individual can only know so many things. Moreover, as ideas accumulate, the division of labor must increase. This point was made by Albert Einstein,<sup>21</sup> and has been repeatedly demonstrated in recent studies showing that increasing specialization and collaboration are generic features across wide areas of knowledge (Jones 2009, Wuchty et al. 2007, Borjas and Doran 2012, Agrawal et al. 2013).

Notably, in this view development becomes innately “skill-biased”, as increasingly differentiated skilled workers embody an expanding set of productivity-enhancing ideas. Allowing for differentiated workers may therefore also resolve tensions between measures of human capital and skill-biased technical change. Moving beyond limited conceptions of human capital that emphasize the quantity and/or quality of a generic “schooling” or “experience” variable (i.e. a perfect-substitutes assessment), we can instead think about skilled workers as vessels of differentiated, advanced knowledge. This perspective in turn suggests a basic theory of development, which can act as a neoclassical synthesis, bringing together concepts of ideas, capital, and institutions into a common framework. I close by considering this interpretation.

#### **4.2.2 Toward a Neoclassical Synthesis**

The generalized analysis of human capital stocks suggests that cross-country output variation can be accounted for without much if any reliance on residual, total factor productivity (TFP) variation. Because TFP is often interpreted as (i) "ideas" and/or (ii) "institutions", this analysis might therefore seem to diminish these explanations for economic development. Such an implication, however, need not follow if ideas are embodied in the capital inputs and the embodiment process is influenced by institutions.

Consider ideas first. Macroeconomic arguments aside, studies of production processes through history suggest that new ideas are central to understanding productivity gains – from agriculture to transportation, from manufacturing to health – as detailed in many

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<sup>21</sup>Einstein observed that “. . . knowledge has become vastly more profound in every department of science. But the assimilative power of the human intellect is and remains strictly limited. Hence it was inevitable that the activity of the individual investigator should be confined to a smaller and smaller section. . . .” (Einstein 1932).

studies.<sup>22</sup> Consistent with this perspective, and the modern endogenous growth literature, one may posit the central role of ideas in driving increased prosperity.

Now consider capital. Studying any particular production process, it seems straightforward that for ideas (e.g. techniques, designs, blueprints, protocols, facts, theories, beliefs) to enter production they must be known and implemented; that is, they must be actuated through tangible inputs. Capital inputs can then be simply defined as the instantiation of ideas. Physical capital inputs (e.g. buildings, tools, airplanes, microprocessors, MRI machines) can be defined as the instantiation of ideas into objects. Human capital inputs (e.g. surgeons, engineers, managers) can be defined as the instantiation of ideas (e.g. surgical, engineering, managerial techniques) into people.<sup>23</sup>

Finally, consider institutions. Putting ideas into production through capital inputs, rather than as a residual, provides tangible processes in which institutions like property rights and contracts matter. Weak institutional environments can naturally underpin failures in acquiring physical and human capital inputs. For example, individuals may collectively fail to embody advanced ideas when faced with high borrowing costs, high coordination costs, and poor educational institutions (Jones 2010 and Online Appendix II). Institutional features like weak contracting environments and poor public good provision can then naturally underpin investment failures.

Together, this perspective can allow one to move beyond some common debates about human capital, ideas, and institutions by seeing them not in contest with each other but as pieces of an integrated structural process. There need be no horse race between these features. Rather, output can be mapped into capital inputs. Capital inputs can be mapped onto ideas. Institutions affect these mappings. In this interpretation, the contribution of this paper is not in reducing the roles of ideas or institutions. The findings are fully consistent with a framework in which investment, ideas, and institutions play essential roles – but

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<sup>22</sup>Mokyr's *The Lever of Riches* (1992) provides many historical examples as do overviews of 20th century U.S. economic growth (e.g. Augustine et al. 2007, Chapter 2, and *The Economic Report of the President* 2011, Chapter 3). Nordhaus (1997) provides a powerful example by studying the price of light through time. Conley and Udry (2010) is one of many studies demonstrating that ideas can fail to diffuse in poor countries.

<sup>23</sup>People are thus differentiated and embody advanced ideas only collectively, as discussed above. The productivity of an individual is thus tied to broader skill complementarities, as allowed in this paper's generalized accounting. Such interactions can happen through explicit production teams (a surgical team, an assembly line), through broader organizations such as firms, and through market interactions. Thus the division of labor perspective can broadly encapsulate concepts of "organizational capital" and other ideas emphasizing collaboration.



where human capital can be drawn to the heart of economic development.

While the framework is applied here to cross-country income differences, the same framework has other natural applications at the level of countries, regions, cities, or firms. Growth accounting provides one direction for future work. The urban-rural economy literature is another direction, where productivity differences from specialization are often suggested as critical but cannot be captured using traditional human capital measures.

## 5 Appendix

### *Proof of Lemma 1*

**Proof.**  $H = G(H_1, H_2, \dots, H_N)$  is constant returns in its inputs (Assumption 1). Therefore, by Euler's theorem for homogeneous functions, the true human capital aggregate can generically be written  $H = \sum_{i=1}^N G_i H_i$ . Rewrite this expression as  $H = G_1 h_1 \sum_{i=1}^N \frac{G_i h_i}{G_1 h_1} L_i$ . Recalling that  $w_i = \frac{\partial F}{\partial H} G_i h_i$  (Assumption 2), so that  $\frac{w_i}{w_1} = \frac{G_i h_i}{G_1 h_1}$ , we can therefore write  $H = G_1 h_1 \tilde{L}_1$ , where  $\tilde{L}_1 = \sum_{i=1}^N \frac{w_i}{w_1} L_i$ . ■

### *Proof of Lemma 2*

**Proof.** If  $H = G(H_1, Z)$  is constant returns to scale, then  $G_1$  is homogeneous of degree zero by Euler's theorem. Therefore  $G_1(H_1, Z) = G_1(H_1/Z, 1)$ . Noting that  $G_{11} \leq 0$ , it follows that  $\Lambda = G_1^R/G_1^P \geq 1$  iff  $Z^R/H_1^R \geq Z^P/H_1^P$ . ■

### *Proof of Lemma 3*

**Proof.** By Lemma 1,  $H = G_1 \tilde{H}$ , providing an independent expression for  $H$  based on its first derivative. If the human capital aggregator can be manipulated into the form  $H = Q(H_1, Z(H_2, \dots, H_N)) = Q(H_1, P(H, H_1))$ , then we have from Lemma 1  $H = Q_1(H_1, P(H, H_1)) \tilde{H}$ . This provides an implicit function determining  $H$  solely as a function of  $H_1$  and  $\tilde{H}$ ; that is, without reference to  $Z(H_2, \dots, H_N)$ . ■

### *Proof of Corollary 1*

**Proof.** By Lemma 1,  $H = G_1 \tilde{H}$ . For the GDL aggregator,  $G_1 = (H/H_1)^{\frac{1}{\varepsilon}}$ . Thus  $H = H_1^{\frac{1}{1-\varepsilon}} \tilde{H}^{\frac{\varepsilon}{\varepsilon-1}}$ . ■

## Data Appendix

### *Capital Stocks*

To minimize sources of difference with standard assessments, this paper uses the same data in Caselli's (2005) review of cross-country income accounting. Income per worker is taken from the Penn World Tables v6.1 (Heston et al. 2002) and uses the 1996 benchmark year. Capital per worker is calculated using the perpetual inventory method,  $K_t = I_t +$

$(1 - \delta)K_{t-1}$ , where the depreciation rate is set to  $\delta = 0.06$  and the initial capital stock is estimated as  $K_0 = I_0/(g + \delta)$ . Further details are given in Section 2.1 of Caselli (2005). As a robustness check, I have also considered calculating capital stocks as the equilibrium value under Assumptions 1 and 2 with a Cobb-Douglas aggregator; i.e.,  $K = (\alpha/r)Y$ , where  $\alpha = 1/3$  is the capital share and  $r = 0.1$ . This alternative method provides similar results as in the main paper.

To calculate human capital stocks, I use Barro and Lee (2001) for the labor supply quantities for those at least 25 years of age, which are provided in five groups: no schooling, some primary, completed primary, some secondary, completed secondary, some tertiary, and completed tertiary. Schooling duration for primary and secondary workers are taken from Caselli and Coleman (2006) and schooling duration for completed tertiary is assumed to be 4 years. Schooling duration for "some" education in a category is assumed to be half the duration for complete education in that category. Figure A2 summarizes the Barro and Lee labor allocation data.

For wage returns to schooling, I use Mincerian coefficients from Psacharopoulos (1994) as interpreted by Caselli (2005). Let  $s$  be the years of schooling and let relative wages be  $w(s) = w(0)e^{\phi s}$ . Psacharopoulos (1994) finds that wage returns per year of schooling are higher in poorer countries, and Caselli summarizes these findings with the following rule. Let  $\phi = 0.13$  for countries with  $\bar{s} \leq 4$ , where  $\bar{s} = (1/L) \sum_{i=1}^N s_i L_i$  is the country's average years schooling. Meanwhile, let  $\phi = 0.10$  for countries with  $4 < \bar{s} \leq 8$ , and let  $\phi = 0.07$  for the most educated countries with  $\bar{s} > 8$ . Unskilled labor equivalents are then calculated as  $\tilde{L}_1 = \sum_{i=1}^N e^{\phi s_i} L_i$  in each country.

As a robustness check, I have considered calculating  $\tilde{H}$  under a variety of other assumptions. The results using the GDL aggregators are broadly robust to reasonable alternatives. The sample mean value of  $\varepsilon$  at which capital stocks fully explain income variation typically falls in the the  $[1.5, 2]$  interval across human capital accounting methods. For example, if we set  $\phi = .10$  (the global average) for all countries, then the gap between unskilled labor equivalents widens slightly, since the returns to education in poor countries now appear lower and the returns in rich countries appear higher. The resulting increase in human capital ratio means that capital inputs can fully explain income differences at somewhat higher values of  $\varepsilon$ , but still with  $\varepsilon < 2$ .

### *Variation in the Quality of Unskilled Labor*

Following the analysis in Section 2.4, the difference in unskilled qualities are estimated as  $h_1^R/h_1^P = w_1^R/w_1^{R|P}$ , where wages are for unskilled workers in the U.S. The term  $w_1^R$  is the mean wage for unskilled workers born in the US and  $w_1^{R|P}$  is the mean wage for unskilled workers born in a poor country and working in the US.

Wages are calculated from the 5% microsample of the 2000 U.S. Census (available from [www.ipums.org](http://www.ipums.org)). Unskilled workers are defined as employed individuals with 4 or less years of primary education (individuals with `educ=1` in the pums data set, which is the lowest schooling-duration group available) who are between the ages of 20 and 65. To facilitate comparisons, mean wages are calculated for individuals who speak English well (individuals with `speakeng=3, 4, or 5` in the pums data set).

Figure A3 presents the data, with the mean wage ratio,  $w_1^{R|P}/w_1^R$ , plotted against log per-capita income of the source country. (National income data is taken from the Penn World Tables v6.1.) There is one observation per source country, but the size of the marker is scaled to the number of observed workers from that source country. The figure plots the results net of fixed effects for gender and each integer age in the sample.

For accounting and regression analysis when relaxing Assumption 4, the (weighted) mean of  $w_1^R/w_1^{R|P}$  is calculated for five groups of immigrants based on quintiles of average schooling duration in the source country. In practice, these corrections adjust  $h_1^R/h_1^P$  modestly when departing from  $h_1^R/h_1^P = 1$ , with a range of 0.87 to 1.20 depending on the quintile. The age and gender controlled data is used, although using the raw wage means produces similar findings. The corrections for  $h_1^R/h_1^P$  are then applied to the human capital stock in each country.

This wage method for estimating  $h_1^R/h_1^P$  operates under the additional premise that immigrant workers are representative of the source country population ( $h_1^{R|P} \approx h_1^P$ ). As discussed in Section 2.4, there is a large literature on immigrant selection, and existing reviews of this literature (Hendricks 2002, Clemens 2011) argue that immigrant selection appears modest. Studies around the world of various source and host country pairs tend to show a mix of modest negative selection (e.g. de Coulon and Piracha 2005; Ibarrran and Lubotsky 2007) and positive selection (e.g. Chiquiar and Hanson 2005; Brucker and Trubswetter 2007; Brucker and Defoort 2009, McKenzie et al. 2010), which is consistent

with the theoretical ambiguity of the matter (e.g. Borjas 1987, McKenzie and Rapoport 2007) and further suggests that there is no large, systematic departure from representative sampling. Some authors argue that there may be tendency toward positive selection on observables (e.g. Hanson 2010), which may extend into unobservables (e.g. McKenzie et al. 2010), in which case the wage adjustment is conservative, providing a lower bound on human capital differences across countries.

While several studies examine populations with low average educational attainment, none to my knowledge explicitly examine the category with four or less years of schooling, which is the group used for the wage adjustment in this paper. I therefore consider additional empirical analysis, examining Mexican migration to the United States. Given that U.S. Census data is used for the wage correction and that Mexicans are the most common immigrant population to the U.S., this population may be especially relevant for this paper. Recent studies using state-of-the-art Mexican microdata find, in consonance with the broader literature, modest degrees of selection and further a mixed direction of selection with slight positive selection from rural areas and slight negative selection from urban areas (Fernandez-Huertas Moraga 2011, 2013; Kaestner and Malamud forthcoming). To examine selection among those with four or less years of education, I have acquired both the Encuesta Nacional de Empleo Trimestral sample used in Fernandez-Huertas Moraga (2011) and the Mexican Family Life Survey sample used in Kaestner and Malamud (forthcoming).<sup>24</sup> Table A1 shows the results, examining the real earnings measures used in these studies and comparing those who migrate to the U.S. with those who stay at home. The analysis finds little selection among migrants using either sample and regardless of age and gender controls. Thus, on the basis of these data, the immigrant sample looks broadly representative.

Overall neither the wage correction using U.S. Census data nor extant evidence about immigrant selection point to a substantial role for Assumption 4. One can use other reasonable methods to calculate  $w_1^R/w_1^{R|P}$  and apply it to the human capital measures, but in general the primary findings of the paper are robust to such variations, because the implications of relaxing Assumption 3 tend to be much greater.

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<sup>24</sup>See their papers for detailed description of the data and their earnings variables.

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**Table 1: Basic Data**

Measure	Rich v Poor		
	99 <sup>th</sup> / 1 <sup>st</sup> Percentile (USA/Zaire)	85 <sup>th</sup> / 15 <sup>th</sup> Percentile (Israel/Kenya)	75 <sup>th</sup> / 25 <sup>th</sup> Percentile (S Korea/India)
$Y^R / Y^P$ (Income)	90.9	16.9	6.3
$K^R / K^P$ (Capital stock)	185.3	43.9	17.4
$\tilde{L}_1^R / \tilde{L}_1^P$ (Unskilled worker equivalents)	1.70	1.33	1.15
$L_1^R / L_1^P$ (Unskilled workers)	.09	.44	.52

Income and capital stock measures are per worker. Data sources and methods are further described in the text and appendix.

**Table 2: Human Capital and Income: Accounting Approach**

	Elasticity of Substitution Between Unskilled Labor, $H_U$ , and Skilled Aggregate, $Z(H_2, \dots, H_N)$						
	1	1.2	1.4	1.6	1.8	2.0	$\infty$
<i>Panel A: Relaxing Assumption 3</i>							
$H^R/H^P$	$\infty$	358	21.9	8.6	5.4	4.1	1.3
$\Lambda$	$\infty$	269	16.4	6.5	4.0	3.1	1
Success	$\infty$	1050%	163%	88%	64%	54%	25%
<hr/>							
<i>Panel B: Relaxing Assumptions 3 and 4</i>							
$H^R/H^P$	$\infty$	306	18.6	7.3	4.6	3.5	1.1
$\Lambda$	$\infty$	269	16.4	6.5	4.0	3.1	1
Success	$\infty$	950%	147%	79%	58%	48%	23%

This table compares Israel and Kenya, which represent the 85<sup>th</sup> and 15<sup>th</sup> percentile countries respectively ranked by income per worker.  $H^R/H^P$  is the ratio of human capital stocks.  $\Lambda$  is the ratio of  $H^R/H^P$  at the indicated elasticity of substitution to  $H^R/H^P$  for the infinite elasticity of substitution case. Success is the consequent percentage of the income variation that is explained by variation in capital inputs. Figure 2 summarizes accounting for a broader set of rich and poor countries and shows that Israel and Kenya provide a useful benchmark, as discussed in the text.

**Table 3: Human Capital and Income: Regression Approach**

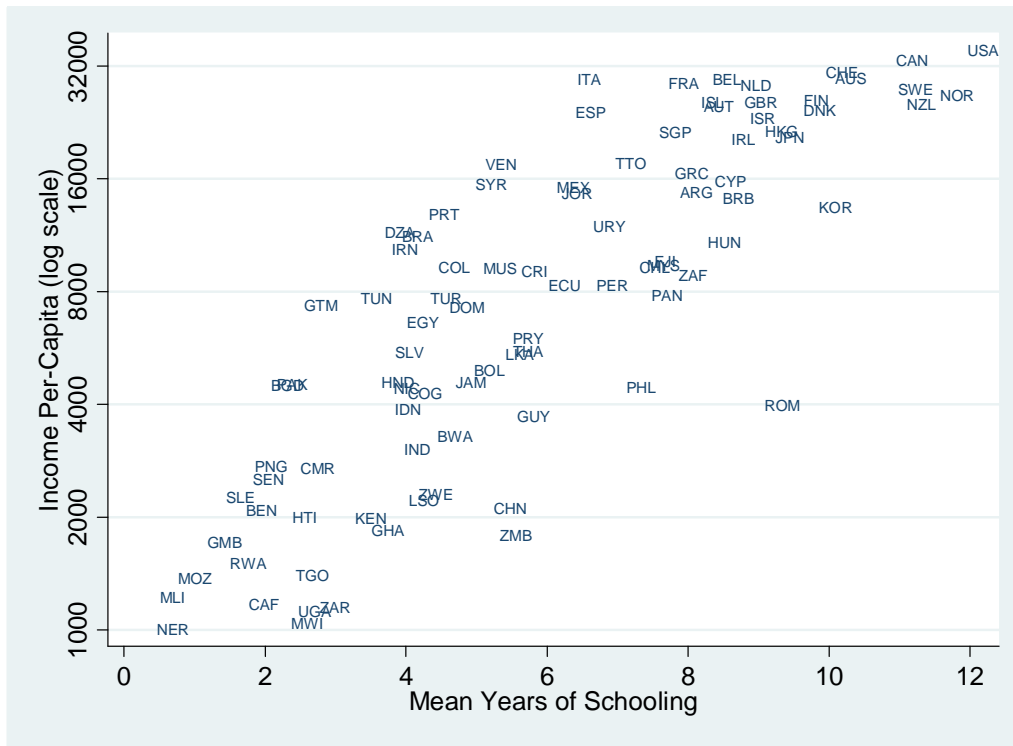
	Dependent variable is $\log \hat{Y}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(\tilde{H})$	2.606** (0.212)		2.049** (0.293)	1.713** (0.143)		1.467** (0.141)
$\log(H_1)$		-0.957** (0.195)	-0.344* (0.158)		-0.762** (0.141)	-0.508** (0.137)
Observations	92	92	92	92	92	92
R-squared	0.508	0.371	0.533	0.445	0.246	0.545
-----						
Implied $\varepsilon$						
(from $\tilde{H}$ )	1.34 [1.28-1.44]	--	1.48 [1.34,1.83]	1.64 [1.50-1.87]	--	1.83 [1.83-2.28]
(from $H_1$ )	--	1.70 [1.50,2.17]	2.94 [2.01,23.3]	--	1.88 [1.64,2.38]	2.31 [1.85,3.82]

Specifications (1) – (3) maintain Assumption 4. Specifications (4) – (6) relax Assumption 4.

Robust standard errors in parentheses. Robust 95% confidence intervals in square brackets.

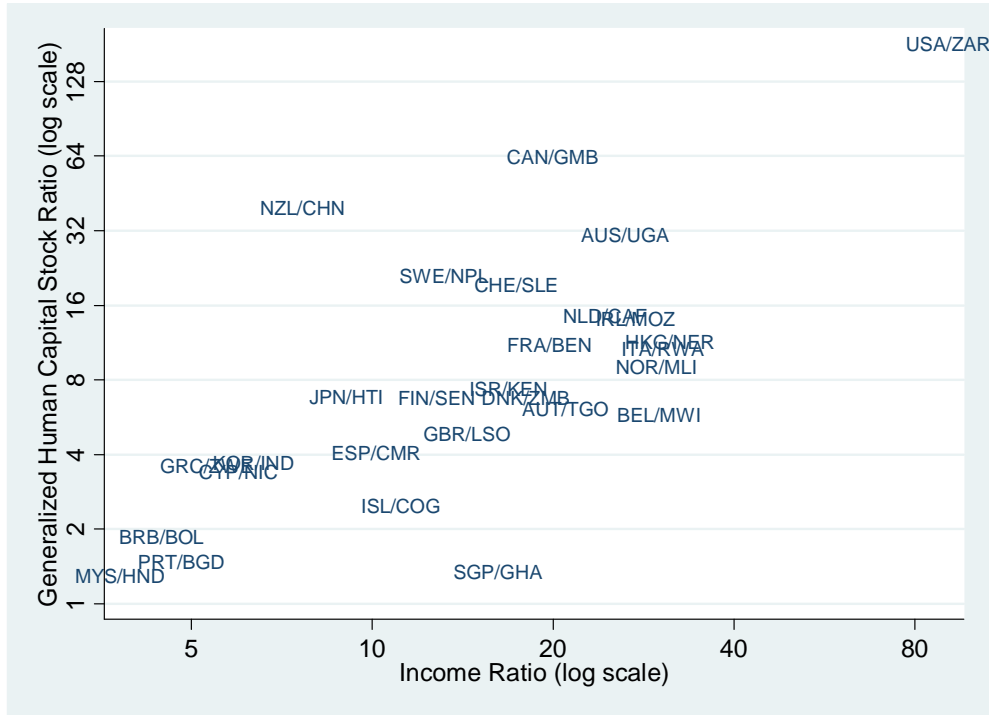
\* indicates  $p < 0.05$ , \*\* indicates  $p < 0.01$

**Figure 1: Income per Worker and Mean Schooling Duration**

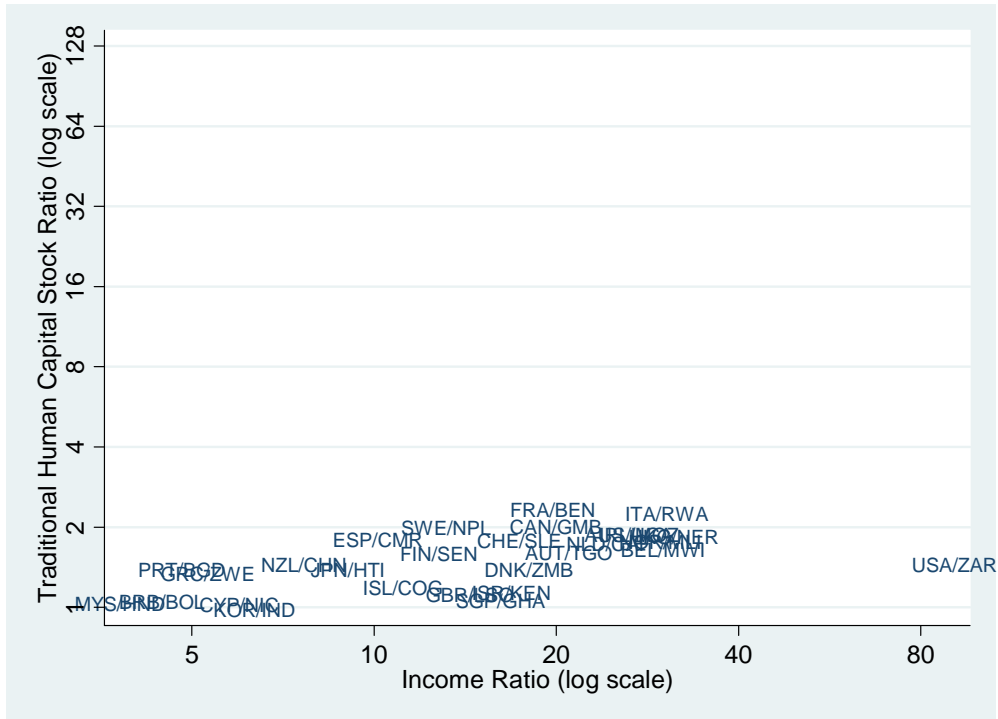


**Figure 2: Human Capital Stock Variation**

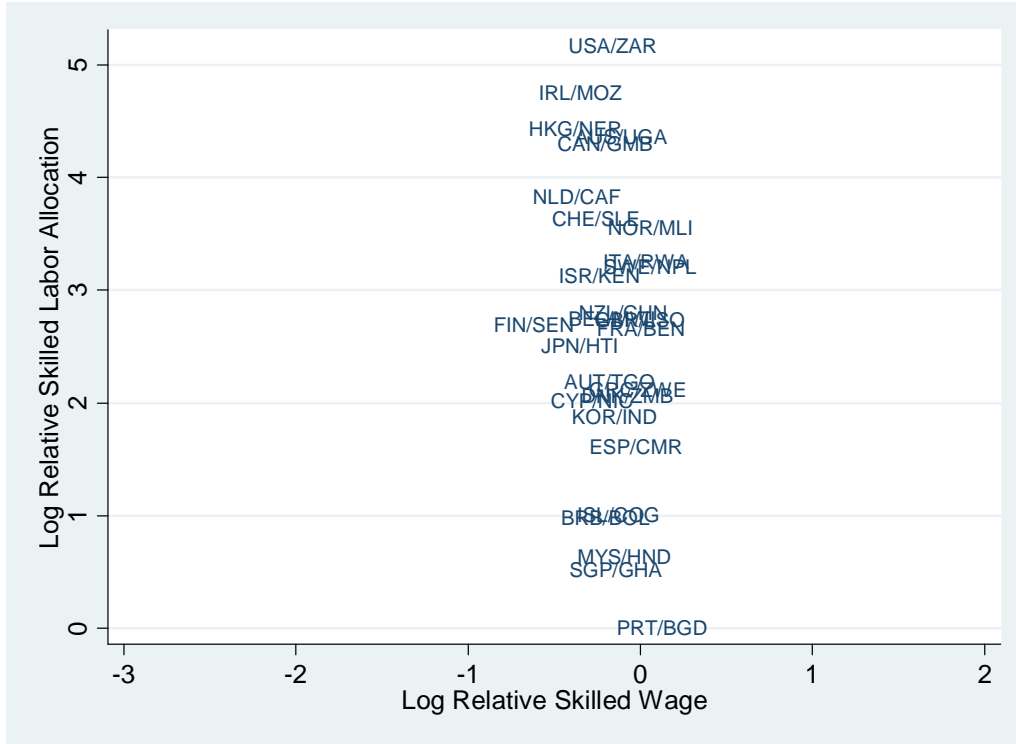
Panel A: Generalized Human Capital Stock



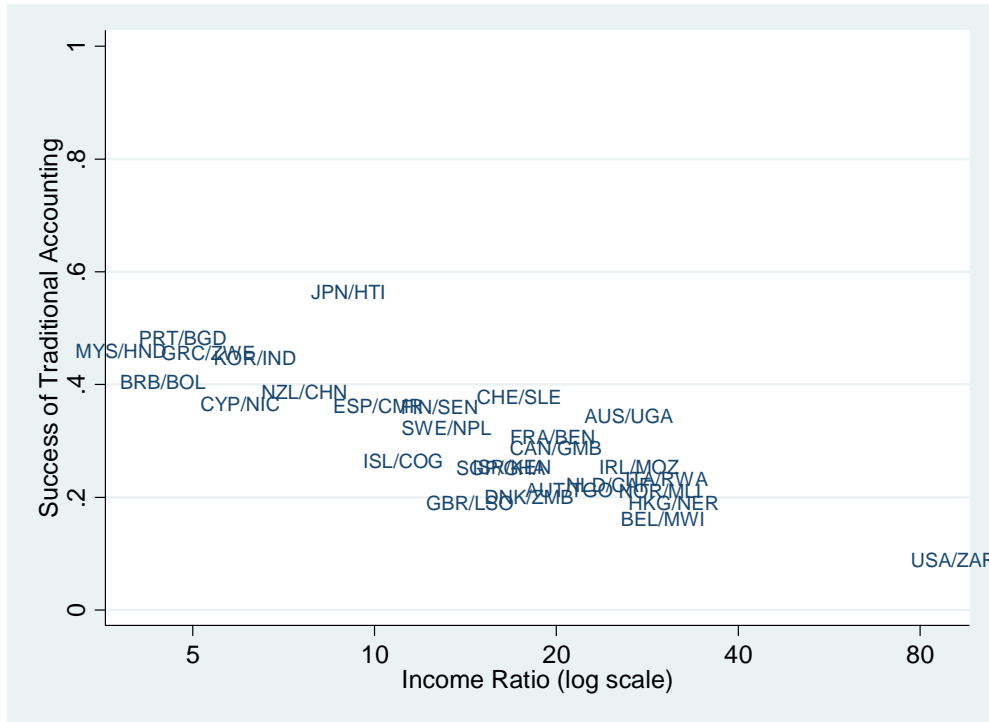
Panel B: Traditional Human Capital Stock



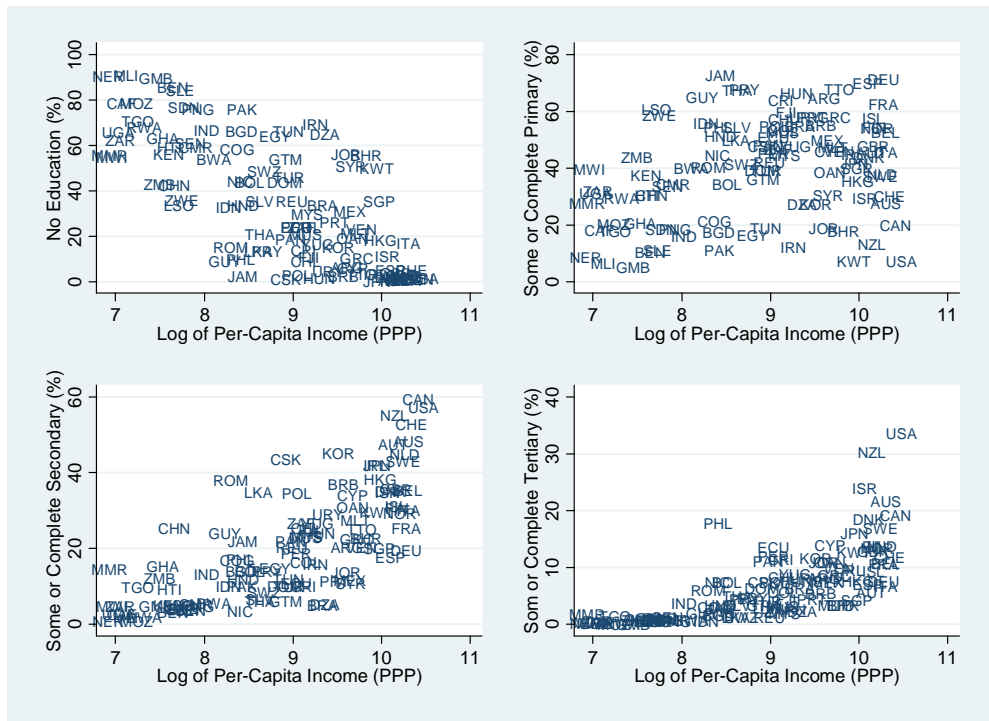
**Figure 3: Sources of Human Capital Variation: Labor Supply versus Wages**



**Figure A1: Fraction of Income Difference Explained Using Traditional Human Capital Accounting**

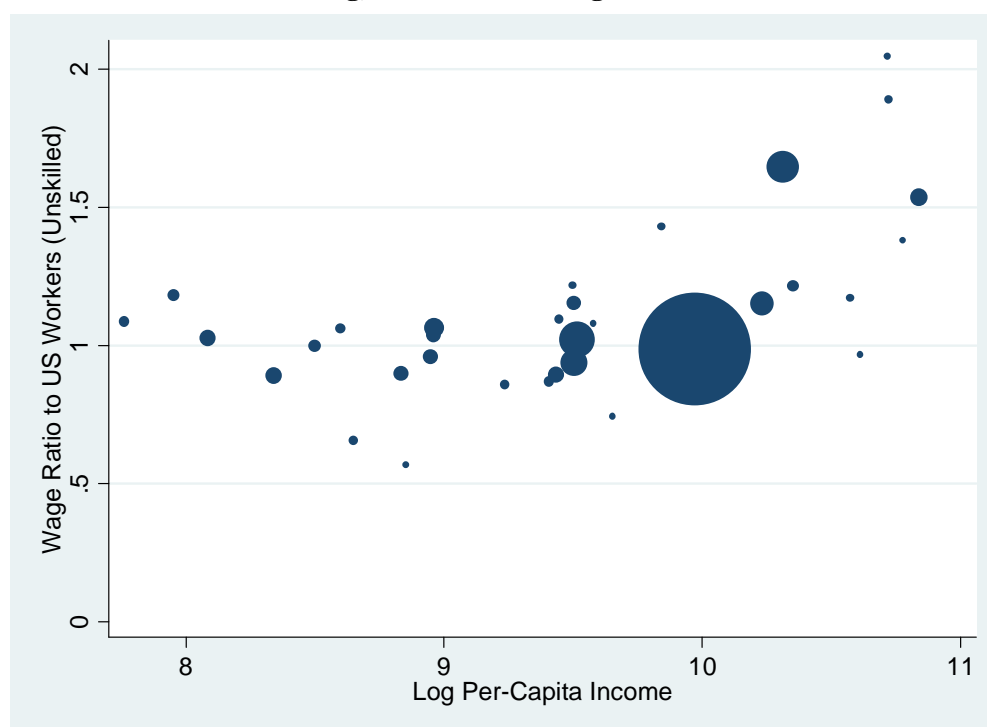


**Figure A2: Fraction of Workers with Given Schooling (from Barro and Lee 2001)**





**Figure A3: Wage Ratios from 2000 US Census among Employed Workers with Four or Less Years of Schooling, Conditional on Age and Gender**



**Table A1: Immigrant Selection, Four or Less Years of Schooling**

	Dependent variable: log earnings							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All	Rural	Urban	All	All	Rural	Urban	All
Migrated to U.S.	-0.0240	0.167***	0.0514	0.00875	0.00931	0.0880	-0.0174	-0.109
Controls <sup>(a)</sup>	(0.0290)	(0.0459)	(0.0325)	(0.0276)	(0.167)	(0.212)	(0.258)	(0.158)
	No	No	No	Yes	No	No	No	Yes
Data	ENET	ENET	ENET	ENET	MxFLS	MxFLS	MxFLS	MxFLS
Observations	429,815	120,633	309,182	429,815	2,253	1,291	962	2,251
R-squared	0.000	0.000	0.000	0.163	0.000	0.000	0.000	0.126

Notes:

<sup>(a)</sup>Controls include fixed effects for each age in years and dummies for gender and rural residency.

I thank Jesus Fernandez-Huertas Moraga and Ofer Malamud for providing access to and guidance on the Encuesta Nacional de Empleo Trimestral (ENET) data and the Mexican Family Life Survey (MxFLS) data, and for sharing their constructed variables. For ENET, earnings are the real hourly wage. For MxFLS, the earnings are real annual earnings, including benefits and income from secondary jobs.

Robust standard errors in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

# The Human Capital Stock: A Generalized Approach

## Online Appendices

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January 2013

### 1 Online Appendix I: Unskilled Workers

This appendix extends the results to different definitions of "unskilled" workers. Recall that the main text estimates the GDL aggregator

$$H = \left[ H_1^{\frac{\varepsilon-1}{\varepsilon}} + Z(H_2, H_3, \dots, H_N)^{\frac{\varepsilon-1}{\varepsilon}} \right]^{\frac{\varepsilon}{\varepsilon-1}} \quad (1)$$

assuming  $H_1$  (unskilled human capital services) are a perfect substitutes aggregation of workers with no more than primary school education. More generally, we can consider (1) different delineations between skilled and unskilled workers, and (2) alternative aggregations among the unskilled. This appendix first extends the theory to allow alternative (and richer) descriptions of unskilled workers and then considers empirical estimates.

#### 1.1 Theory

We group as "unskilled" a variety of different workers. Their labor services can be defined generally as

$$H_1 = Q(H_{11}, H_{12}, \dots, H_{1J})$$

across  $J$  sub-types of unskilled workers (e.g. those with no formal education, those with some primary education, etc.). Under Assumptions 1 and 2, Lemma 1 applies to  $Q(\cdot)$ , so that we can equivalently write

$$H_1 = Q_1 \tilde{H}_1 \quad (2)$$

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where  $\tilde{H}_1 = h_{11}\tilde{L}_1$  and  $\tilde{L}_1 = \sum_{j=1}^J \frac{w_{1j}}{w_{11}} L_{1j}$ .

Under a perfect substitutes assumption,  $H_1 = \tilde{H}_1$ . This is the approach used in the main text. Such an approach is conservative. That is, it limits human capital differences across countries, following the same reasoning as discussed throughout the paper. For example, if we write

$$H_1 = Q(H_{11}, W(H_{12}, \dots, H_{1J}))$$

then Lemma 2 also applies: since poor countries are relatively abundant in the lowest skill group (e.g. those with no schooling), relaxing the perfect substitutes assumption among the unskilled will elevate  $H_1^R/H_1^P$ . As with the general reasoning in the paper, this implication follows prior to consideration of precise functional forms or data. Other things equal this relaxation will elevate  $H^R/H^P$ .

To proceed to specific empirical analysis, we can consider the generalization

$$H_1 = \left[ H_{11}^{\frac{\mu-1}{\mu}} + W(H_{12}, \dots, H_{1J})^{\frac{\mu-1}{\mu}} \right]^{\frac{\mu}{\mu-1}}$$

among unskilled workers. Coupled with the aggregator (1) used in the primary analysis and using (2), we can (after some algebra) equivalently write the human capital stock as

$$\hat{H} = h_{11}L_{11} \left( \tilde{L}_1/L_{11} \right)^{\frac{\mu}{\mu-1}} (\tilde{L}/\tilde{L}_1)^{\frac{\varepsilon}{\varepsilon-1}} \quad (3)$$

where  $L_{11}$  is the mass of the least skilled category,  $h_{11}$  is their innate skill,  $\tilde{L}_1$  is a perfect substitutes aggregation among the unskilled, defined above, and  $\tilde{L}$  is the traditional perfect substitutes aggregation of all skill classes defined in the main text. Note that as  $\mu \rightarrow \infty$ , this calculation of  $H$  becomes equivalent to the simpler GDL calculation in the main text, where sub-classes of the unskilled are treated as perfect substitutes. As  $\mu \rightarrow \infty$  and  $\varepsilon \rightarrow \infty$ , we return to the standard perfect substitutes calculation used in traditional accounting.

## 1.2 Empirical Estimation

We can now consider the calculation of human capital stocks, varying (i) the division of labor categories between skilled and unskilled groups, and (ii) the aggregation of these based on  $\varepsilon$  and  $\mu$ .

### 1.2.1 Accounting

Recall the definition of  $\Lambda$  from the main text, measuring the ratio of generalized human capital differences to the traditional perfect-substitutes calculation. Using (3), the amplification of human capital differences is

$$\Lambda = \frac{L_{11}^R}{L_{11}^P} \left( \frac{\tilde{L}_1^R/L_{11}^R}{\tilde{L}_1^P/L_{11}^P} \right)^{\frac{\mu}{\mu-1}} \left( \frac{\tilde{L}^R/\tilde{L}_1^R}{\tilde{L}^P/\tilde{L}_1^P} \right)^{\frac{\varepsilon}{\varepsilon-1}} \frac{\tilde{L}^P}{\tilde{L}^R}$$

Similarly, recall that the metric *success*, which measures the percentage of cross-country output variation predicted by variation in capital inputs, is

$$success = \Lambda^{1-\alpha} \times success_T$$

where *success<sub>T</sub>* is the success percentage under traditional accounting. These measures can be calculated for any particular rich-poor country pair.

Figures A1.1-A1.6 present  $\Lambda$  and *success* across countries given various  $(\varepsilon, \mu)$  pairs and various delineations between unskilled and skilled workers. As in the main text, the measure is calculated for all country pairs from the 70/30 to 99/1 percentiles in per-capita income. The mean amplification of human capital differences and mean success rate across countries is then presented for each set of parameters. Unskilled labor is defined using six different delineations, using the finest gradations available from the Barro-Lee data: (1) no schooling (Figure A1.1); (2) some primary or less schooling (Figure A1.2); (3) completed primary or less schooling (Figure A1.3); (4) some secondary or less schooling (Figure A1.4); (5) completed secondary or less schooling (Figure A1.5); and (6) some tertiary or less schooling (Figure A1.6).

Several observations can be made. First, looking across these figures, it is clear that the generalized accounting substantially elevates human capital differences and can help explain cross-country income variation with much higher levels of *success* over a wide space of parameters and delineations between skilled and unskilled labor. Second, the human capital amplification increases as either  $\mu$  or  $\varepsilon$  falls – i.e. as we move away from perfect substitutes. Third, higher cutoffs between skilled and unskilled workers produce a given success value at lower values of  $\varepsilon$  and/or  $\mu$ . Put another way, as we expand the unskilled category, the success measure increasingly depends on  $\mu$ . This finding is natural: treating workers as perfect substitutes diminishes human capital variation and, as we move more workers

into the unskilled category, how we treat these workers increasingly matters. Broadly, we see that the capacity to substantially expand the role of human capital in development accounting appears regardless of the skill cutoff.

### 1.2.2 Regression

The generalized accounting elevates human capital differences across countries. However, the specific extent of this amplification depends on  $\varepsilon$  and  $\mu$ . Defining unskilled workers as those with completed secondary or less schooling, the within-country micro-literature suggests  $\varepsilon \in [1, 2]$  with commonly reported estimates suggesting  $\varepsilon \approx 1.5$ . Estimates of  $\varepsilon$  for other categorizations of the unskilled and estimates of  $\mu$  do not appear available. Thus picking  $(\varepsilon, \mu)$  definitively awaits further research. However, with appropriate identification caveats, one may see how simple regressions estimate these parameter values.

To proceed, we can further relax the regression approach used in the main text. With the human capital measure generalized as in (3), the regression becomes

$$\log \hat{Y}^c = \beta_0 + \beta_1 \log \tilde{L}_1^c / L_{11}^c + \beta_2 \log \tilde{L}^c / \tilde{L}_1^c + \beta_3 \log H_{11}^c + u^c \quad (4)$$

where  $\beta_1 = \frac{\mu(1-\alpha)}{\mu-1}$ ,  $\beta_2 = \frac{\varepsilon(1-\alpha)}{\varepsilon-1}$ , and  $\beta_3 = 1 - \alpha$ . This model introduces greater parametric flexibility, allowing separate estimation of  $\varepsilon$  and  $\mu$ . Whereas the regression model in the main text over-identifies  $\varepsilon$  (under the assumption that  $\mu = \infty$ ), the regression model (4) relaxes the restriction on  $\mu$  and estimates this parameter as well.

Table A1.1 presents the results from estimating (4). Each column considers a different delineation between skilled and unskilled workers, as indicated at the top of each column. Panel A estimates  $(\varepsilon, \mu)$  under the restricted model where we assert  $\alpha = 1/3$ , while Panel B relaxes this assumption and estimates the triple  $(\varepsilon, \mu, \alpha)$ .

One may make several observations. First, raising the threshold between unskilled and skilled workers produces lower estimates of  $\varepsilon$ . This finding suggests that complementarities between skilled and unskilled workers appear greatest when we isolate the very highly skilled. Importantly, looking at column 5, which corresponds to the secondary versus tertiary schooling delineation in the extant micro-literature, we see  $\hat{\varepsilon} = 1.5$ , which is very similar to that literature's estimates. Second, the point estimates show a higher elasticity of substitution among unskilled workers, with  $\hat{\mu} \approx 4$  being typical. This finding suggests

that unskilled workers are more substitutable among themselves than they are with skilled workers, which seems natural. Third, the regressions in Panel B also suggest reasonable estimates of  $1 - \hat{\alpha}$ , with point estimates centering around 0.6, which is broadly consistent with observed labor shares (Gollin 2002, Bernanke & Gurkaynak 2002).

Figure A1.7 takes the estimates of the  $\varepsilon$  and  $\mu$  from each regression (i.e. for each classification of skilled workers) and examines the relevant accounting calculations at these parameter values. In the upper panel of Figure A1.7, we see that human capital differences across country pairs increase on average by a factor of 3.4 to 7.1 depending on the delineation between skilled and unskilled workers. The lower panel shows that the *success* measure ranges from 72% to 109%. Examining the "Completed Secondary" case, where available estimates in the micro-literature provide within-country IV estimates that are consistent with  $\varepsilon = 1.5$ , human capital differences across countries increase by a factor of 4.7 and the success measure is 88%. Thus, regardless of the delineation between skilled and unskilled workers, we see large amplifications of human capital differences across countries and, correspondingly, a capacity to explain most or all of the income variation across countries.

## 2 Online Appendix II: Skilled Workers

A value of the human capital stock calculations in the text is that they do not require detailed specification of the aggregator and are robust to any constant-returns specification  $Z(H_1, H_2, \dots, H_N)$ . At the same time, it is useful to look "underneath the hood" and gain a better understanding of where the variation in stocks may come from. This Online Appendix proceeds in two parts. First, it explores variation in skill returns across countries. As discussed in Section 3.5, the productivity gains (in output) associated with skill appear far larger in rich than poor countries. This appendix provides explicit estimates of this variation and considers simple equilibrium reasoning to show why large variation in skill returns across countries is consistent with modest variation in wage returns (Figure 3). Second, this appendix examines a concrete explanation for the relatively enormous skill returns in rich countries, emphasizing their greater collective acquisition of knowledge. This approach, the "division of labor hypothesis", provides a natural link between human capital and skill-bias, while allowing a simple calibration.

### 2.1 Variation in Skilled Labor Services

Under Assumptions 1 and 2, the relative flow of services for two groups of laborers in an economy is

$$\frac{h_i}{h_j} = \frac{w_i G_j}{w_j G_i} \quad (5)$$

as shown in the main text, where  $h_i = H_i/L_i$  is the mean flow of services from the workers in group  $i$ . Thus the relative service flows  $(h_i/h_j)$ , which are in units of output, can in general be inferred from relative wages  $(w_i/w_j)$  and the relative prices of these intermediate human capital services  $(G_j/G_i)$ . Under traditional accounting, skill returns are mapped purely from wage returns, because a perfect substitutes assumption turns off considerations of  $G_j/G_i$ . Under generalized accounting, one must also consider these relative prices.

In particular, with downward sloping demand, a relative abundance of skilled over unskilled services in rich countries will cause the relative price of skilled to unskilled services to fall. From Figure 3, we know that there are very large differences in skilled labor supply across countries but only small differences in wage returns. Given (5), this empirical observation suggests that variation in  $(G_j/G_i)$  rather than variation in  $(w_i/w_j)$  will tend to have the larger implications for understanding variation in service flows  $(h_i/h_j)$ .

To estimate the variation in output gains associated with skill, we can again use the human capital stock estimation approach of Section 3. Using the GDL aggregator in tandem with (5), one can infer the skilled-unskilled ratio of mean service flows as

$$\frac{h_z^R/h_1^R}{h_z^P/h_1^P} = \left( \frac{w_z^R/w_1^R}{w_z^P/w_1^P} \right)^{\frac{\varepsilon}{\varepsilon-1}} \left( \frac{L_z^R/L_1^R}{L_z^P/L_1^P} \right)^{\frac{1}{\varepsilon-1}} \quad (6)$$

where  $h_z = Z(H_2, H_3, \dots, H_N)/L_Z$  is the mean flow of services from skilled workers.

Table A2.1 (Panel A) reports the implied variation in  $h_z/h_1$ , continuing with the rich-poor example in Table 2. Recall that human capital stock variation eliminates residual total factor productivity variation when  $\varepsilon \approx 1.6$ , which is consistent with the regression point estimate in column 4 of Table 3. At this value of  $\varepsilon$ , the relative service flows of skilled workers in the rich country appear 98.6 times larger than in the poor country. This empirical finding is consistent with Caselli and Coleman (2006), but now explicitly extended to the general class of skilled labor aggregators,  $Z(H_2, H_3, \dots, H_N)$ . Thus similar wage returns are consistent with massive differences in labor allocation when skilled service flows are substantially higher in rich countries.

Skilled service flows can be further articulated by specifying particular skilled aggregators,  $Z$ . For example, consider a sub-aggregator of skilled types

$$Z = \left[ \sum_{i=2}^N H_i^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}} \quad (7)$$

where  $\eta$  is the elasticity of substitution among these types. Table A2.1 (Panel B) presents the implied service flows from these different groups of skilled workers.<sup>1</sup> Taking a range of  $\eta \in [1.2, 2]$ , the implied skill return advantages for skilled but less than tertiary-educated workers in the rich country are in the interval [69, 103], while the skill returns among the tertiary-educated are in the interval [60, 284]. In sum, the labor allocations and wage returns evidence in Figure 3 are reconciled when service flows from higher educated workers in rich countries are far higher (as a group) than their service flows in poor countries.

<sup>1</sup>The returns for the sub-groups of workers are calculated using (7) as

$$\frac{h_{i \neq 1}}{h_1} = \left( \frac{w_i}{w_1} \right)^{\frac{\eta}{\eta-1}} \left( \frac{L_i}{L_1} \right)^{\frac{1}{\eta-1}} \left( \frac{h_Z}{h_1} \frac{L_Z}{L_1} \right)^{\frac{\eta-\varepsilon}{\varepsilon(\eta-1)}}$$

The calculations in Panel B of Table A2.1 assume  $\varepsilon = 1.6$  in the GDL aggregator; i.e. the value of  $\varepsilon$  where capital variation fully explains the income variation.



### 2.1.1 Further Intuition from Equilibrium Reasoning

To further interpret these findings, it is useful to consider why the world looks like Figure 3, where there is little variation in wage returns across countries. A simple interpretation lies in endogenous labor supply. To see this, consider a stylized theory where workers choose their education level to maximize their income.

**Assumption 1** *Let individual income,  $y$ , as a function of educational duration,  $s$ , be  $y(s, \theta) = \int_s^\infty w(s, \theta)e^{-rt} dt$  where  $\theta$  is an individual specific parameter. Let individuals maximize income with respect to educational duration.*

In this setting, the individual will choose a personally optimal level of education such that

$$\frac{\partial w / \partial s}{w} = r \tag{8}$$

In other words, the individual's wage return will be log-linear in educational duration at their optimal schooling choice, with a return of  $r\%$ .<sup>2</sup> This log-linearity looks like a Mincerian return. It is also independent of the mapping between skill and schooling. That is, the individual's wage return will settle here according to (8) regardless of how schooling and skill map together. If more schooling brought wage gains above  $r$  for some individuals, these individuals would naturally seek more education, causing the price of the higher-schooling labor services to fall until each individual's equilibrium wage return (8) returned to  $r$ . While moving from individual wage returns to economy-wide wage returns requires some further assumptions, it is clear that simple equilibrium reasoning constrains wage variation. Hence, we may expect the limited wage return variation across countries seen in Figure 3, even as skill returns can vary enormously. Thus wage returns can act to mask rather than reveal variation in skill returns. This equilibrium reasoning provides an additional perspective on the data. It also provides an additional perspective on the problem underlying traditional human capital accounting, which assumes that wage returns on their own can guide human capital inferences.

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<sup>2</sup>A richer maximization problem can introduce other features besides the discount rate, such as tax rates, tuition rates, and life expectancy, which will further influence the equilibrium wage return (see, e.g., Card 2003 or Heckman et al. 2006 for richer descriptions). The simple version in the text is close to Willis (1986).

## 2.2 The Division of Labor

In advanced economies, and especially among the highly educated, skills appear highly differentiated. Not only do skills differ across medical doctors, chemical engineers, computer scientists, molecular biologists, lawyers, and architects, but skills within professions can be highly differentiated themselves. The U.S. Census recognizes over 31,000 different occupational titles. Measures of knowledge suggest similar specialization; the U.S. Patent and Trademark Office indexes 475 primary technology classes and 165,000 subclasses, while the Web of Science and PubMed together index over 15,000 science and engineering journals. A now large micro-literature documents extensive and increasing labor division and collaboration across wide areas of knowledge (Jones 2009, Wuchty et al. 2007, Borjas and Doran 2012, Agrawal et al. 2013). To the extent that the set of productive knowledge is too large for any one person to know, the division of labor can be seen as necessary to achieve advanced productivity.

This section considers greater task specialization as a possible explanation for the greater skilled service flows in rich countries. In particular, we unpack the skilled aggregator  $Z(\cdot)$ . The approach provides a simple theory and calibration exercise to show how differences in labor division can provide the 100-fold productivity differences seen in Table A2.1, thus incorporating the classic idea that the division of labor may be a primary source of economic prosperity (e.g., Smith 1776). The approach also builds on ideas in a related paper (Jones 2010), which considers micro-mechanisms that can obstruct collective specialization among skilled workers, linking ideas, human capital, and skill-bias into a common framework.

The core idea is that focused training and experience can provide extremely large skill gains at specific tasks. For example, the willingness to pay a thoracic surgeon to perform heart surgery is likely orders of magnitude larger than the willingness to pay a dermatologist (or a Ph.D. economist!) to perform that task. Similarly, when building a microprocessor fabrication plant, the service flows from appropriate, specialized engineers are likely orders of magnitude greater than could be achieved otherwise. Put another way, if no individual can be an expert at everything, then embodying the stock of productive knowledge (i.e. "ideas") into the workforce requires a division of labor. Possible limits to task specialization include: (i) the extent of the market (e.g. Smith 1776); (ii) coordination costs across workers (e.g. Becker and Murphy 1992); (iii) the extent of existing advanced knowledge (Jones 2009); and

(iv) local access to advanced knowledge (e.g. Jones 2010). In addition to poor access to high-quality tertiary education, the capacity to access advanced knowledge may be limited by low-quality primary and secondary schooling in poor countries, for which there is substantial evidence (e.g. Hanushek and Woessmann 2008, Schoellman 2012). The following set-up is closest theoretically to Becker and Murphy (1992) and Jones (2010), while further providing a path toward calibration consistent with the human capital stock estimates in this paper.

### 2.2.1 Production with Specialized Skills

Consider skilled production as the performance of a wide range of tasks, indexed over a unit interval. Production can draw on a group of  $n$  individuals. With  $n$  individuals, each member of the group can focus on learning an interval  $1/n$  of the tasks. This specialization allows the individual to focus her training on a smaller set of tasks, increasing her mastery at this set of tasks. If an individual devotes a total of  $s$  units of time to learning, then the time spent learning each task is  $ns$ .

Let the skill at each task be defined by a function  $f(ns)$  where  $f'(ns) > 0$ . Meanwhile, let there be a coordination penalty  $c(n)$  for working in a team. Let task services aggregate with a constant returns to scale production function that is symmetric in its inputs, so that the per-capita output of a team of skilled workers with breadth  $1/n$  will be  $h(n, s) = c(n)f(ns)$ . We assume that  $c'(n) < 0$ , so that bigger teams face larger coordination costs, acting to limit the desired degree of specialization.<sup>3</sup>

Next consider the choice of  $s$  and  $n$  that maximizes the discounted value of skilled services per-capita.<sup>4</sup> This maximization problem is

$$\max_{s,n} \int_s^\infty h(n, s) e^{-rt} dt$$

### 2.2.2 Example

Let  $c(n) = e^{-\theta n}$ , where  $\theta$  captures the degree of coordination costs that ensue with greater labor division. Let  $f(ns) = \alpha(ns)^\beta$ , where  $\alpha$  and  $\beta$  are educational technology parameters.

<sup>3</sup>For analytical convenience, we will let team size,  $n$ , be a continuous variable.

<sup>4</sup>Decentralized actors may not necessarily achieve this symmetric, output maximizing outcome. In fact, given the presence of complementarities across workers, multiple equilibria are possible (see Jones 2010). Here we consider the output maximizing case as a useful benchmark.

It follows from the above maximization problem that<sup>5</sup>

$$s^* = \beta/r \tag{9}$$

$$n^* = \beta/\theta \tag{10}$$

and skilled services per-capita are  $e^{-\beta} \alpha \left(\frac{\beta^2}{r\theta}\right)^\beta$ . Expertise at tasks declines with higher discount rates ( $r$ ), which reduce the length of education, and with greater coordination costs ( $\theta$ ), which limit specialization.

As a simple benchmark, assume common  $\beta$  around the world. Then the ratio of skilled labor services between a rich and poor country will be

$$\frac{h^R}{h^P} = \frac{\alpha^R}{\alpha^P} \left(\frac{r^P \theta^P}{r^R \theta^R}\right)^\beta \tag{11}$$

This model thus suggests a complementarity of mechanisms. Differences in the quality of education ( $\alpha$ ), discount rates ( $r$ ), and coordination penalties ( $\theta$ ) have multiplicative effects. These interacting channels provide compounding means by which skilled labor services may differ substantially across economies.

### 2.2.3 Calibration Illustration

We focus on the division of labor. Note from (10) that with common  $\beta$  the equilibrium difference in the division of labor (that is, the team size ratio) is equivalent to the inverse coordination cost ratio,  $\theta^P/\theta^R$ . To calibrate the model, let  $\beta = 2.2$ , which follows if the duration of schooling among the highly educated is 22 years and the discount rate is 0.1. Further let  $\alpha^R/\alpha^P = 1$  and take the Mincerian coefficients as those used to calculate each country's human capital stocks throughout the paper, as described in the Data Appendix. Figure A2.1 then plots the implied variation in the division of labor,  $n^R/n^P$ , that reconciles (11) with the quality variation  $h_z^R/h_z^P$  implied by (6), under the assumption that rich countries have no advantage in education technology.

We find that a 4.3-fold difference in the division of labor can explain the productivity difference between Israel and Kenya (the 85-15 percentile country comparison), and a 2.4-fold difference explains the productivity difference between Korea and India (the 75-25 percentile country comparison). The extreme case of the USA and the former Zaire is explained with a

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<sup>5</sup>The following stationary points are unique, and it is straightforward to show that they satisfy the conditions for a maximum.

22-fold difference. These differences would fall to the extent that the education technology  $(\alpha, \beta)$  is superior in richer countries.

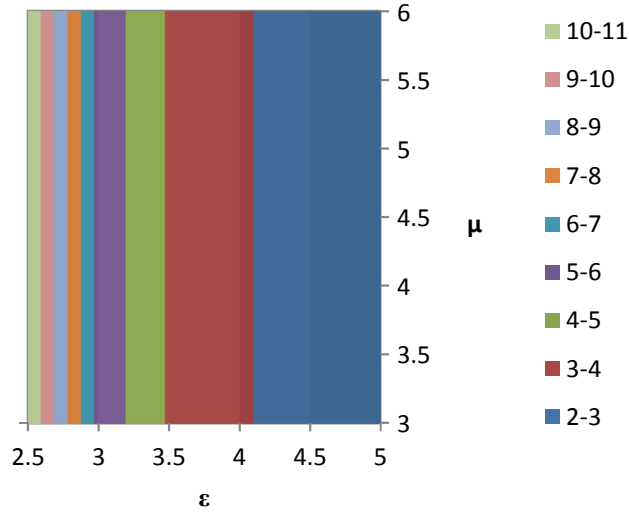
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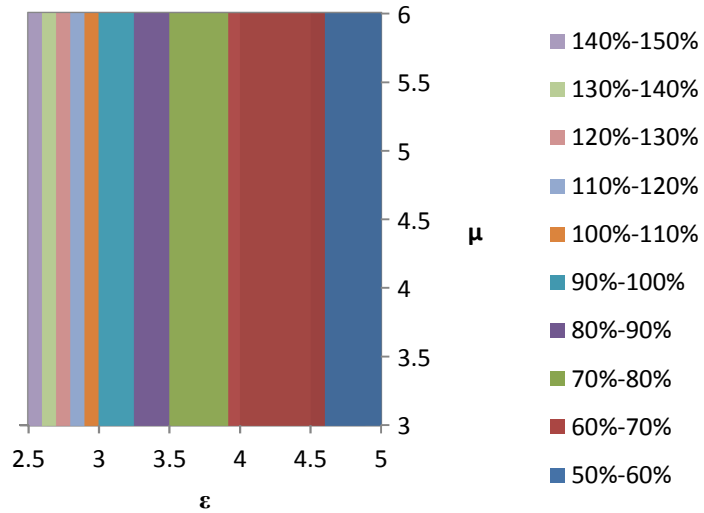
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**Figure A1.1: Generalized Accounting, Unskilled Have No Education**

$\Lambda$  (Amplification of human capital differences)



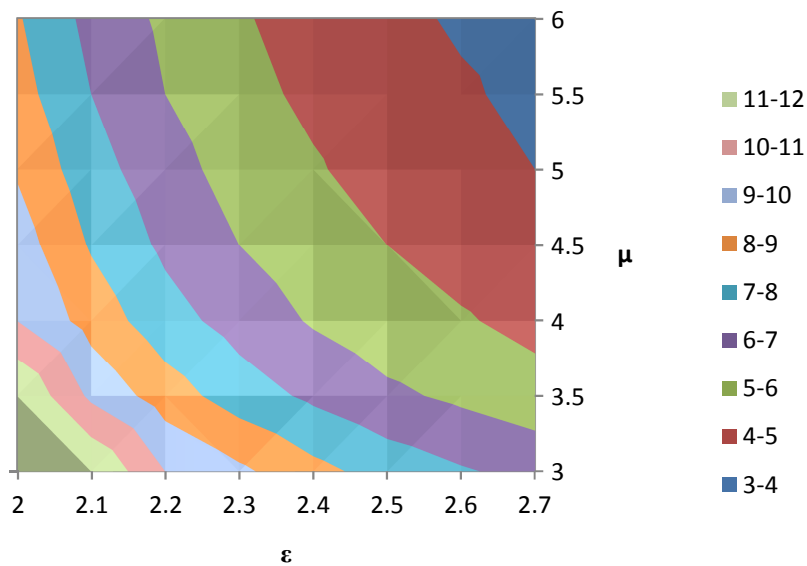
Success (Percentage of income variation explained)



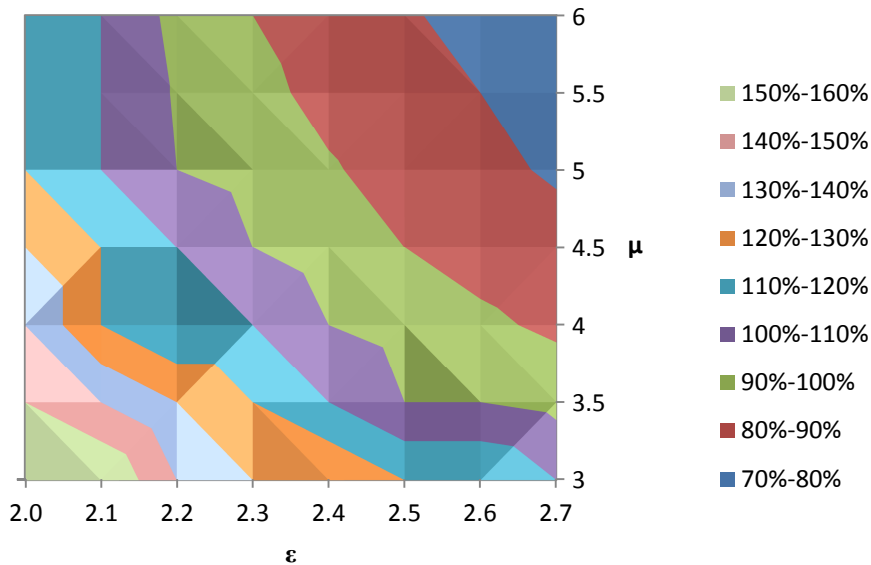
Notes: The upper panel presents the measure  $\Lambda$ , which is the ratio of the generalized human capital differences to traditional human capital differences. The lower panel presents the measure “success”, which is the percentage of the income variation explained by capital input variation. In both panels, at a given  $\epsilon$  and  $\mu$ , the mean of each measure is presented across all pairs of countries from the 70/30 to the 99/1 percentiles of income differences. In this figure, which defines the unskilled as those with no education, the parameter  $\mu$  plays no role.

**Figure A1.2: Generalized Accounting, Unskilled Have Some Primary or Less Education**

$\Lambda$  (Amplification of human capital differences)



Success (Percentage of income variation explained)

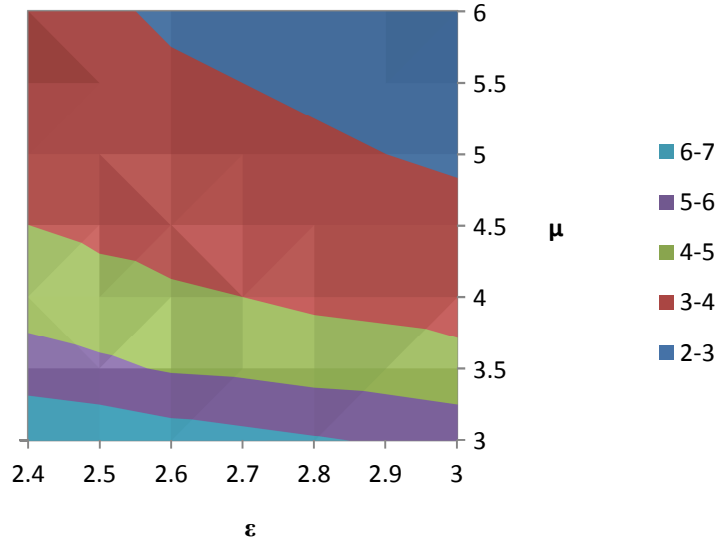


Notes: The upper panel presents the measure  $\Lambda$ , which is the ratio of the generalized human capital differences to traditional human capital differences. The lower panel presents the measure “success”, which is the percentage of the income variation explained by capital input variation. In both panels, at a given  $\epsilon$  and  $\mu$ , the mean of each measure is presented across all pairs of countries from the 70/30 to the 99/1 percentiles of income differences.

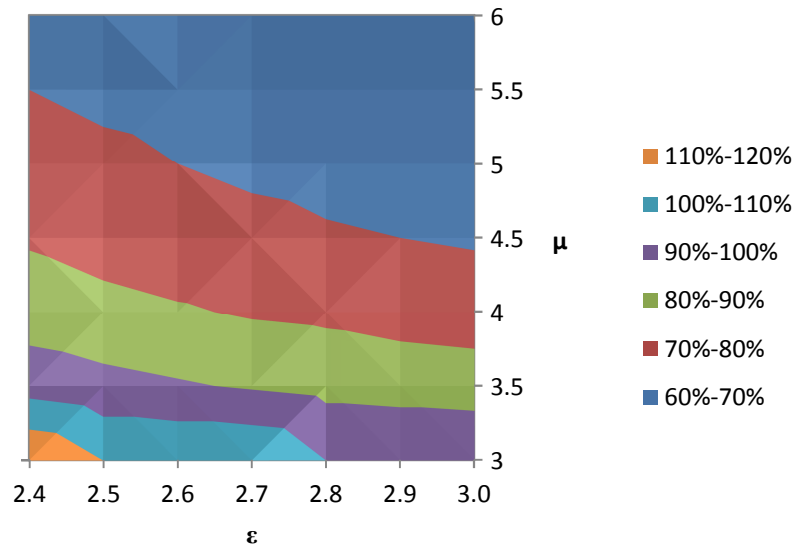


**Figure A1.3: Generalized Accounting, Unskilled Have Complete Primary or Less Education**

$\Lambda$  (Amplification of human capital differences)



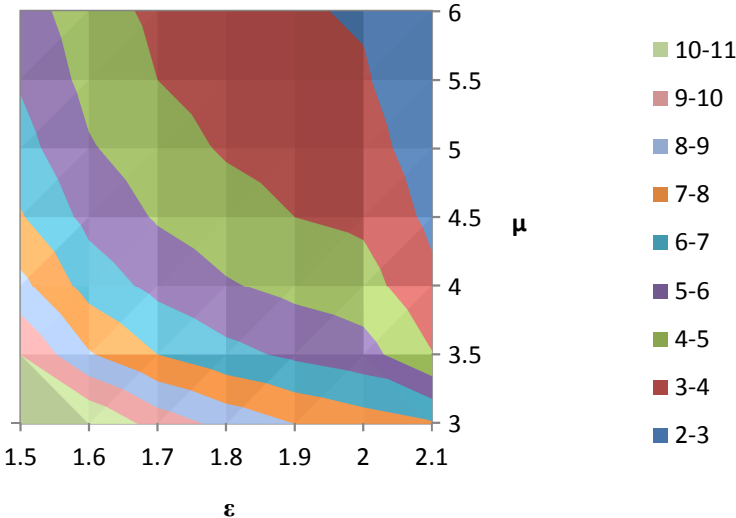
Success (Percentage of income variation explained)



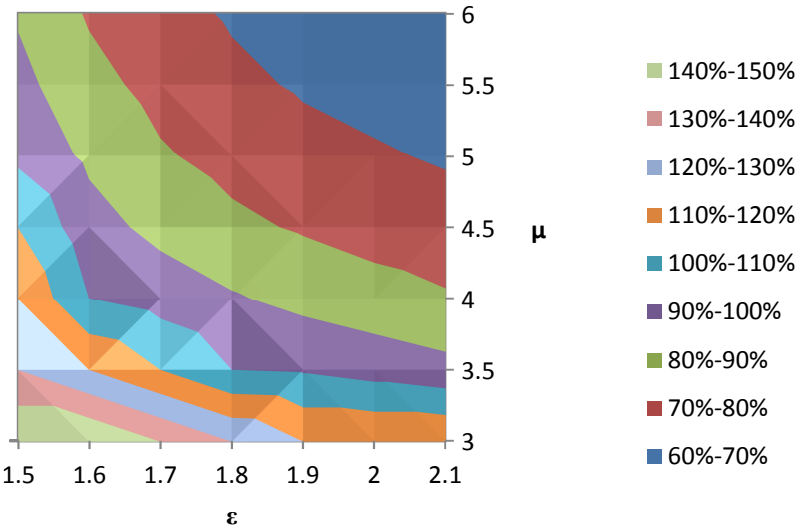
Notes: The upper panel presents the measure  $\Lambda$ , which is the ratio of the generalized human capital differences to traditional human capital differences. The lower panel presents the measure “success”, which is the percentage of the income variation explained by capital input variation. In both panels, at a given  $\epsilon$  and  $\mu$ , the mean of each measure is presented across all pairs of countries from the 70/30 to the 99/1 percentiles of income differences.

**Figure A1.4: Generalized Accounting, Unskilled Have Some Secondary or Less Education**

$\Lambda$  (Amplification of human capital differences)



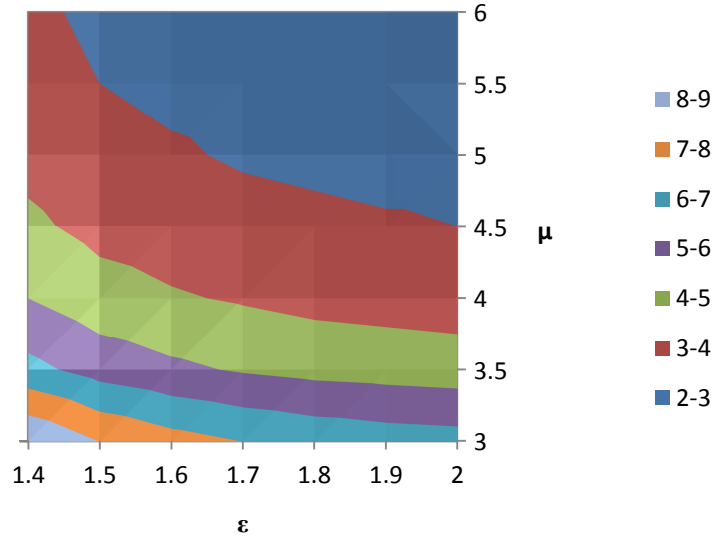
Success (Percentage of income variation explained)



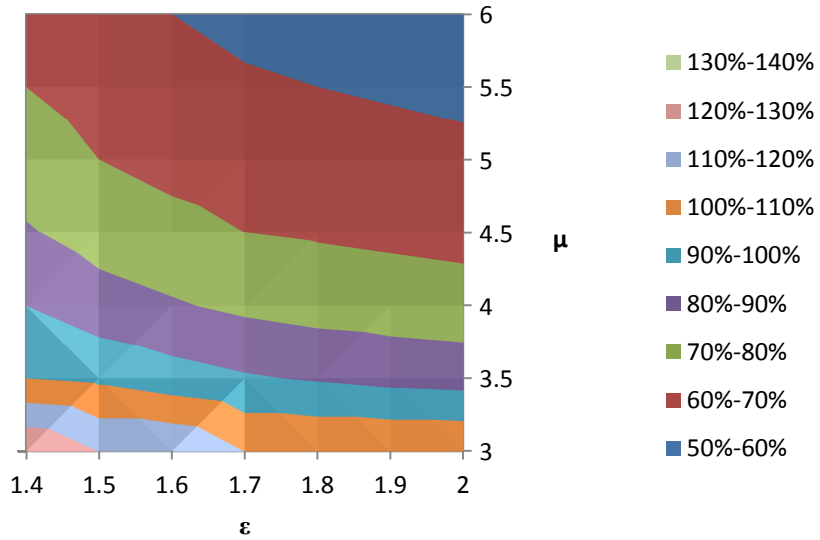
Notes: The upper panel presents the measure  $\Lambda$ , which is the ratio of the generalized human capital differences to traditional human capital differences. The lower panel presents the measure “success”, which is the percentage of the income variation explained by capital input variation. In both panels, at a given  $\epsilon$  and  $\mu$ , the mean of each measure is presented across all pairs of countries from the 70/30 to the 99/1 percentiles of income differences.

**Figure A1.5: Generalized Accounting, Unskilled Have Complete Secondary or Less Education**

$\Lambda$  (Amplification of human capital differences)



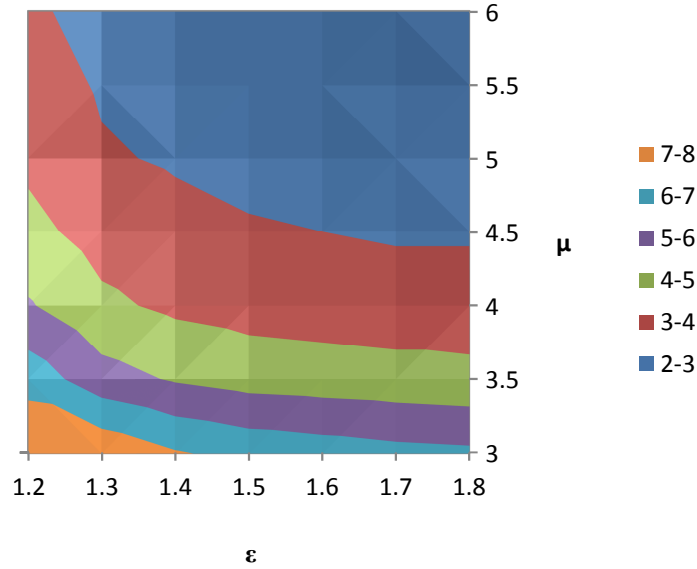
Success (Percentage of income variation explained)



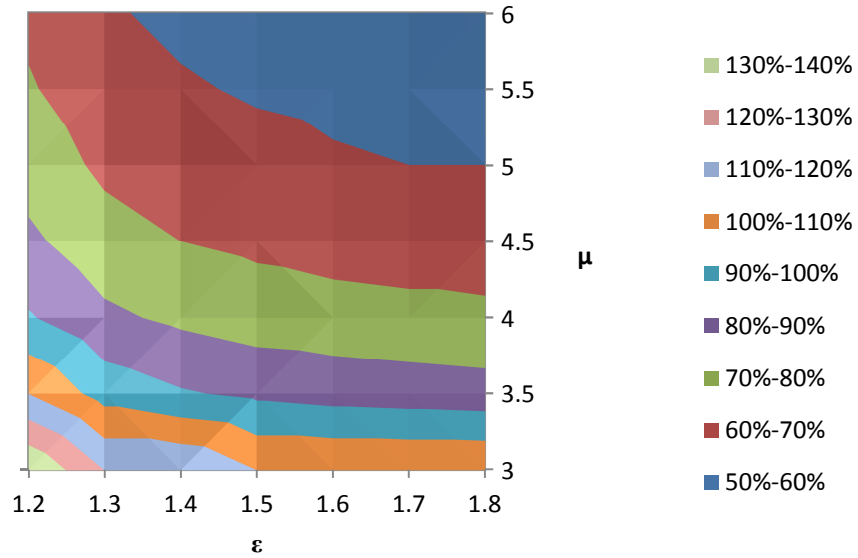
Notes: The upper panel presents the measure  $\Lambda$ , which is the ratio of the generalized human capital differences to traditional human capital differences. The lower panel presents the measure “success”, which is the percentage of the income variation explained by capital input variation. In both panels, at a given  $\epsilon$  and  $\mu$ , the mean of each measure is presented across all pairs of countries from the 70/30 to the 99/1 percentiles of income differences.

**Figure A1.6: Generalized Accounting, Unskilled Have Some Tertiary or Less Education**

$\Lambda$  (Amplification of human capital differences)

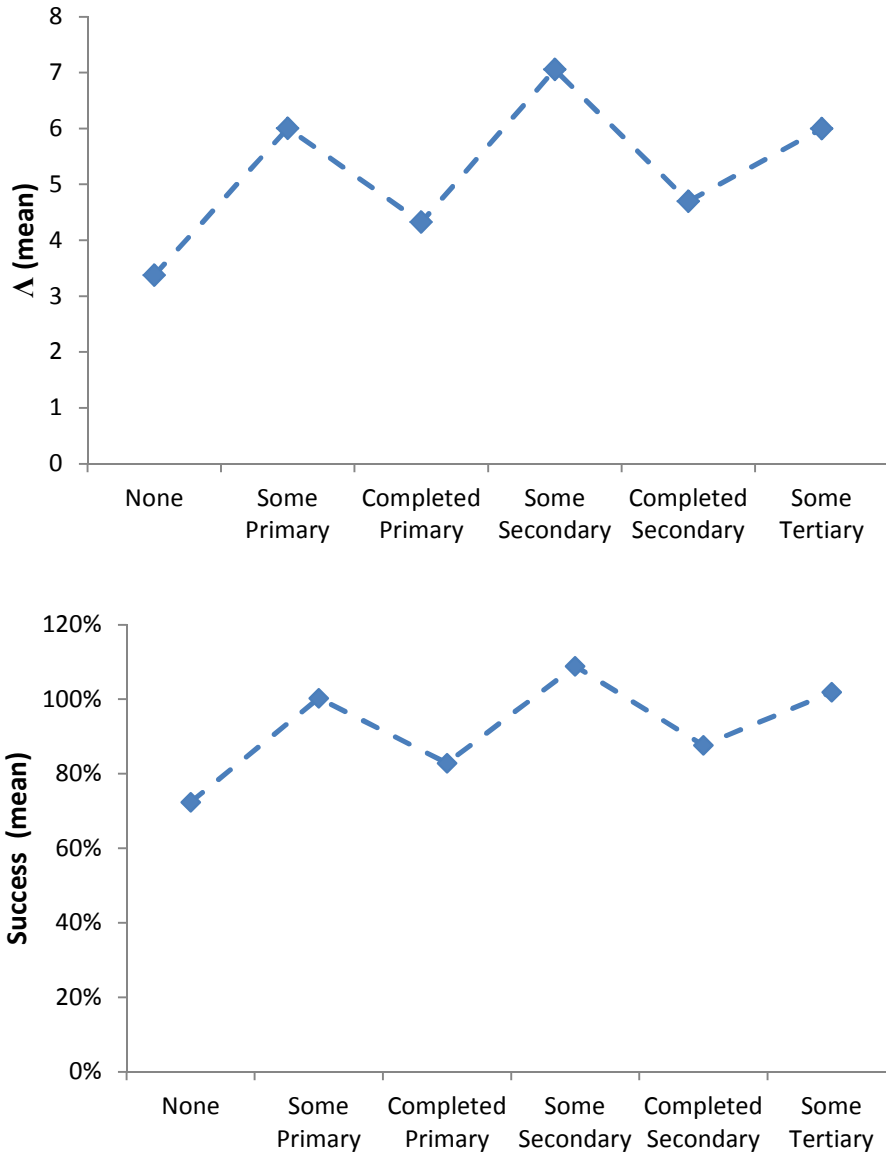


Success (Percentage of income variation explained)



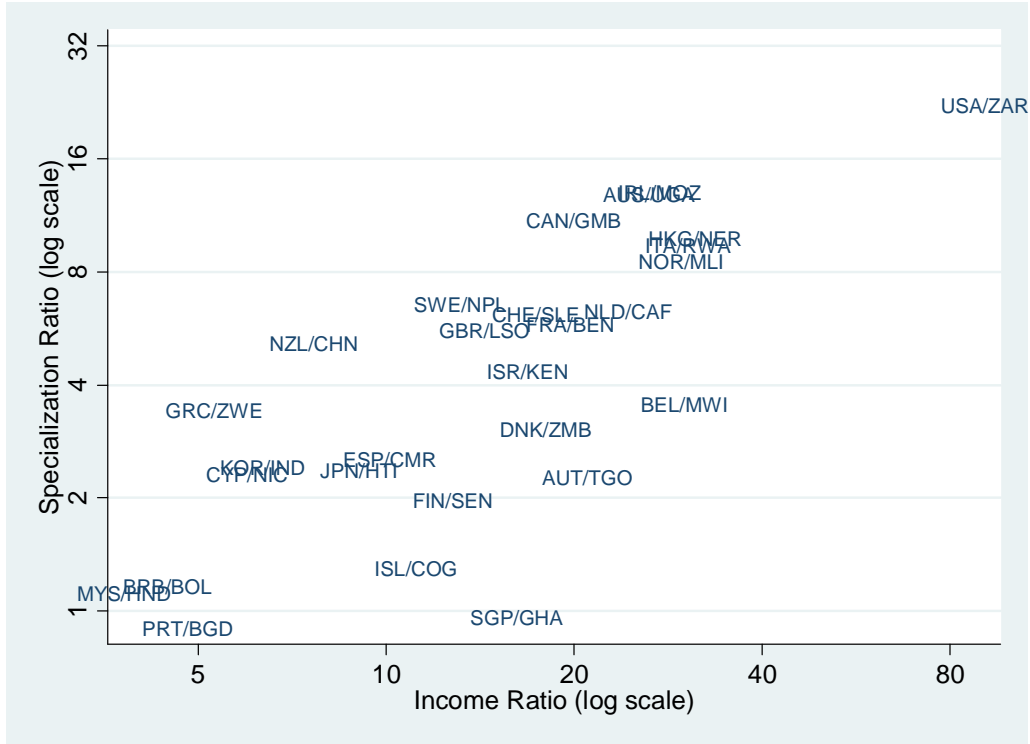
Notes: The upper panel presents the measure  $\Lambda$ , which is the ratio of the generalized human capital differences to traditional human capital differences. The lower panel presents the measure “success”, which is the percentage of the income variation explained by capital input variation. In both panels, at a given  $\varepsilon$  and  $\mu$ , the mean of each measure is presented across all pairs of countries from the 70/30 to the 99/1 percentiles of income differences.

**Figure A1.7: Human Capital Accounting Using Regression Parameter Estimates**



Note: The x-axis indicates the threshold taken between unskilled and skilled workers, where a category (e.g. “Completed Primary”) means that level of education and below are counted as unskilled. The upper panel presents the ratio of the generalized human capital differences to the traditional perfect-substitutes measure. It uses the regression estimates for  $\varepsilon$  and  $\mu$  from the relevant column in Table A1.B. The lower panel considers the success measure. Means are taken over all pairs of countries from the 70/30 to the 99/1 percentiles of income differences.

**Figure A2.1: Calibrated Difference in Specialization across Countries**



**Table A1.1: Regression Estimates of  $\varepsilon$  and  $\mu$** Panel A: Asserting  $\alpha = 1/3$ 

	(1) No Schooling	(2) Some Primary	(3) Completed Primary	(4) Some Secondary	(5) Completed Secondary	(6) Some Tertiary
$\log(\widetilde{H}_1/H_{11})$	0.949*** (0.0252)	1.117*** (0.0875)	1.113*** (0.116)	1.550*** (0.259)	1.946*** (0.547)	3.005*** (0.891)
$\log(\widetilde{H}/\widetilde{H}_1)$	--	0.823*** (0.0503)	0.892*** (0.0376)	0.859*** (0.0385)	0.892*** (0.0330)	0.894*** (0.0308)
Observations	56	56	56	56	56	56
R-squared	0.948	0.953	0.950	0.954	0.951	0.951
Implied $\varepsilon$	3.36 [3.01-3.87]	2.48 [2.07-3.41]	2.49 [1.99-4.10]	1.76 [1.48-2.81]	1.52 [1.28-4.45]	1.29 [1.16-2.17]
Implied $\mu$	--	5.26 [3.60-12.8]	3.96 [3.22-5.42]	4.47 [3.48-6.77]	3.95 [3.29-5.16]	3.93 [3.31-5.00]

Panel B: Regression estimates of  $\alpha$ 

	(1) No Schooling	(2) Some Primary	(3) Completed Primary	(4) Some Secondary	(5) Completed Secondary	(6) Some Tertiary
$\log(\widetilde{H}_1/H_{11})$	1.030*** (0.258)	1.055*** (0.244)	1.117*** (0.262)	1.476*** (0.309)	1.939*** (0.547)	3.033*** (0.927)
$\log(\widetilde{H}/\widetilde{H}_1)$	0 (0)	0.753*** (0.276)	0.897*** (0.272)	0.757** (0.285)	0.876*** (0.292)	0.816** (0.313)
$\log(H_{11})$	0.758** (0.305)	0.592* (0.300)	0.672** (0.310)	0.557* (0.315)	0.649* (0.327)	0.582 (0.350)
Observations	56	56	56	56	56	56
R-squared	0.732	0.756	0.742	0.760	0.743	0.747
Implied $\varepsilon$	3.79 [1.97-∞]	2.28 [1.62-∞]	2.51 [1.7-∞]	1.61 [1.36-2.82]	1.50 [1.27-4.18]	1.24 [1.14-1.95]
Implied $\mu$	--	4.66 [1.83-]	3.99 [1.88-]	3.77 [1.73-]	3.85 [1.80-]	3.48 [1.68-]

Robust standard errors in parentheses

\*\*\* p&lt;0.01, \*\* p&lt;0.05, \* p&lt;0.1

Notes: The upper panel assumes  $\alpha=1/3$  and adjusts the dependent variable under that assumption. The lower panel lets the regression estimate  $\alpha$  instead. See discussion in the appendix text for the regression models.

**Table A2.1: Human Capital Services by Educational Groups**

<i>Panel A: Human capital services, grouping secondary and tertiary educated workers</i>						
	Elasticity of Substitution Between Unskilled Labor, $H_1$ , and Skilled Aggregate, $Z(H_2, \dots, H_N)$					
	1	1.4	1.6	1.8	2	$\infty$
$\frac{(h_z / h_1)^R}{(h_z / h_1)^P}$	$\infty$	1101	98.6	29.5	14.3	0.79
<i>Panel B: Human capital services, secondary and tertiary educated workers treated separately</i>						
	Elasticity of Substitution Between Secondary, $H_2$ , and Tertiary, $H_3$ , Human Capital Services					
	1.2	1.4	1.6	1.8	2	$\infty$
$\frac{(h_2 / h_1)^R}{(h_2 / h_1)^P}$	68.5	83.9	89.8	92.9	94.8	103
$\frac{(h_3 / h_1)^R}{(h_3 / h_1)^P}$	284	130	100	88.0	81.4	59.6

This table compares Israel and Kenya, which represent the 85<sup>th</sup> and 15<sup>th</sup> percentile countries respectively ranked by income per worker. Panel A of this table corresponds to Panel A of Table 2. Panel B considers the implied human capital services for secondary and tertiary educated workers, depending on the elasticity of substitution between their services. In Panel B, the elasticity of substitution in the GDL aggregator is taken to be 1.6 following the results in the main text.