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The Human Capital Stock: A Generalized Approach*

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Abstract

This paper reconsiders the traditional approach to human capital measurement in the study of cross-country income differences. Within a broader class of neoclassical human capital aggregators, traditional accounting is found to be a theoretical lower bound on human capital differences across economies. Implementing a generalized accounting empirically illustrates the possibility that capital variation may now account (even fully) for the large income variation between rich and poor countries. These findings reject the constraints on human capital variation that traditional accounting has imposed.

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

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This paper reconsiders the traditional method for measuring human capital. A generalized framework for human capital accounting is developed in which workers provide differentiated labor services. Under this framework, human capital variation can account for a much bigger part of cross-country income differences than traditional accounting allows.

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 for cross-country development accounting is Cobb-Douglas. In a seminal paper, Mankiw, Romer, and Weil (1992) used average schooling duration to measure human capital and showed its strong correlation with per-capita output (see Figure 1). Overall, Mankiw, Romer, and Weil's regression analysis found that physical and human capital variation predicted 80% of the income variation across countries.

While the correlation between per-capita income and average schooling is strong, the interpretation of this correlation is not obvious 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.

[Insert Figure 1 about here.]

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 $H = G(H_1, H_2, \ldots H_N)$, 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)

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

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 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 variation appears to account for very little of the large income variation we see.[1] 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 ($G_{1j \neq 1} > 0$).[2] 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

[1] 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 less than 2 (see, e.g., the review of Caselli 2005).

[2] 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 fertizilation, 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).

conditions under which traditional human capital accounting is downward biased, providing only a lower bound on human capital differences across countries. This theoretical result, 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" human capital aggregator. This aggregator features a constant-returns-to-scale aggregation of skilled labor types, $Z(H_2, H_3..., H_N)$, that combines with unskilled labor services with constant elasticity of substitution. This generalized approach allows the human capital stock to 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. The generalized approach can also allow for imperfect substitution among lower-skill workers. This aggregation approach also encompasses traditional human capital accounting as a special case, allowing straightforward comparisons with the traditional results. Using this aggregator, illustrative accounting estimates suggest that human capital variation can be substantially amplified, including to the point where capital variation could possibly fully account for cross-country income differences.

This paper is organized as follows. Section I provides the theoretical results, analyzing traditional human capital measurement in the context of broader neoclassical aggregators. This section develops the core theoretical results. Section II considers empirical implementations in the development accounting context and closes by discussing intuition, interpretations, and open issues. Section III summarizes and points toward further applications. 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 (2011). 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 (2011) 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.

I. Generalized Human Capital Accounting

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 $H = G(H_1, H_2, .., H_N)$ is aggregate human capital, $K = S(K_1, K_2, .., K_M)$ is aggregate 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.

A. 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, $\{L_1, L_2, ..., L_N\}$, we do not easily observe their service flows, $\{h_1, h_2, ..., h_N\}$.

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, $\{w_1, w_2, ..., w_N\}$.

The marginal products assumption implies

$$w_i = \frac{\partial F}{\partial H} G_i h_i \tag{2}$$

where w_i is the wage of labor type i.[3] 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.[4]

To proceed, one may write the wage ratio

$$\frac{w_i}{w_j} = \frac{G_i}{G_j}\frac{h_i}{h_j} \tag{3}$$

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

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

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, $\{G_1/G_2, ..., G_1/G_N\}$. 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.

B. Traditional 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, $Y = K^{a}(AH)^{1-\alpha}$, where α is the physical capital share of income, K is a scalar aggregate capital stock, and $H = G(H_1, H_2, ..., H_N)$ is a scalar human capital aggregate.

[3] 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.

[4] 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).

In practice, the labor types $i = 1, ..., N$ 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 appear to 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 $\{G_1/G_2, ..., G_1/G_N\}$ 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.

C. Generalized Accounting

We now return to a generic human capital aggregator $H = G(H_1, H_2, ..., H_N)$, which nests the traditional perfect-substitutes accounting as a special case.

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

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.*[5]

[5] 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.

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 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 $H = G(H_1, Z(H_2, ..., H_N))$ 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.

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. Building from the results in the prior section, we begin by developing an approach that requires relatively little structure on the relationships among skilled workers. We then consider similar methods and extensions for low-skill workers.

To implement a feasible, generalized accounting, consider first the following lemma.

Lemma 3 *Consider the class of human capital aggregators* $H = G(H_1, Z(H_2, ..., H_N))$. *If such an aggregator can be inverted to write* $Z(H_2, ..., H_N) = P(H, H_1)$*, 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, $Z(H_2, H_3..., H_N)$, 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*

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

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,* $Z(H_2, H_3..., H_N)$.

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 (2011) 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 $Z(H_2, H_3..., H_N)$. 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 $Z(H_2, H_3..., H_N)$.

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 $Z(H_2, H_3..., H_N)$. 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.

Given the Corollary, the implementation of the GDL aggregator becomes

$$\frac{H^R}{H^P} = \frac{h_1^R}{h_1^P}\left(\frac{L_1^R}{L_1^P}\right)^{\frac{1}{1-\varepsilon}}\left(\frac{\tilde{L}_1^R}{\tilde{L}_1^P}\right)^{\frac{\varepsilon}{\varepsilon-1}} \tag{6}$$

In implementing this accounting, a simple way to proceed is to assume that workers have the same innate skill, h_1, across economies (Assumption 4 above). Then the accounting can proceed from measures of L_1, $\tilde{L}_1$, and ε. This generalized approach will be examined empirically in Section II. We will see the possibility of substantial amplification of human capital variation so that, under some parameterizations, human capital may replace total factor productivity residuals in accounting for cross-country income variation.

Additionally, one may also attempt to relax Assumption 4 and allow h_1 to vary across economies.[6] To relax Assumption 4, one can draw on the insights of Hendricks (2002), noting that immigration allows one to observe lower skilled workers from both a rich and poor country in the same economy, thus controlling for broader economic differences that may otherwise cloud inferences about innate skill. Examining immigrants and native-born workers in the rich economy, one may observe the wage ratio

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

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.

If the unskilled immigrants are a representative sample of the unskilled in the poor country, then $h_1^{R|P} = h_1^P$. Therefore $h_1^R/h_1^P = w_1^R/w_1^{R|P}$, which can be used in (6), allowing estimation to proceed. Of course, one may imagine that unskilled immigrants might not be representative of the source country's low skilled population. If immigration selects on higher ability among the unskilled in the source country, then $h_1^{R|P} > h_1^P$ and the co rrection $w_1^R/w_1^{R|P}$ would then be conservative, providing a lower bound on human capital differences across countries.[7]

[6] For example, children in a rich country might have initial advantages (including better nutrition and/or other investments prior to starting school), suggesting $h_1^R > h_1^P$. On the other hand, those with little schooling are a relatively small part of the population in rich countries, suggesting a possible selection effect. If those with very little education in rich countries select on relatively low innate ability, than we might imagine $h_1^R < h_1^P$.

[7] Hendricks (2002) and Clemens (2011) review the extant literature and conclude that immigrant selection

Generalized Lower-Skill Services One may additionally consider more general approaches to measuring lower skill, depending on what kinds of workers are grouped as lower skill and how one aggregates skills among these subgroups. For example, "lower skill" might span from those with no education to those with high school education in some formulations. Aggregation assumptions among these workers will naturally matter more as more skill classes are grouped together.

Lower-skilled labor services can be defined generally as $H_1 = Q(H_{11}, H_{12}, ..., H_{1J})$ across J sub-types of lower-skill workers. The perfect substitutes aggregation for the low-skilled is then $\tilde{H}_1 = h_{11}\tilde{L}_{11}$, where $\tilde{L}_{11} = \sum_{j=1}^{J} \frac{w_{1j}}{w11} L_{1j}$. To generalize in practice, one can implement $H_1 = \left[H_{11}^{\frac{\mu-1}{\mu}} + W(H_{12}, ..., H_{1J})^{\frac{\mu-1}{\mu}} \right]^{\frac{\mu}{\mu-1}}$, following the insights above. Coupled with the aggregator (5), the accounting becomes

$$\frac{H^R}{H^P} = \frac{h_{11}^R}{h_{11}^P} \frac{L_{11}^R}{L_{11}^P} \left(\frac{\tilde{L}_{11}^R / L_{11}^R}{\tilde{L}_{11}^P / L_{11}^P} \right)^{\frac{\mu}{\mu-1}} \left(\frac{\tilde{L}_1^R / \tilde{L}_{11}^R}{\tilde{L}_1^P / \tilde{L}_{11}^P} \right)^{\frac{\varepsilon}{\varepsilon-1}} \tag{8}$$

providing a further generalization that additionally allows scarcity and complementarities to operate across sub-groups of lower-skilled workers. In this further generalization, one may again follow the traditional approach and assert that h_{11} does not vary across economies or, alternatively, estimate it using wage data as above. The estimations in Section II consider a range of approaches.

II. Empirical Estimation

Given the theoretical results, we now reconsider human capital variation and its capacity to account for cross-country income variation. The analysis implements the generalized aggregator developed in Section I.C and emphasizes comparison with the traditional special case.

appears too mild to meaningfully affect human capital accounting. The Data Appendix further reviews this literature and also presents analysis using state-of-the art microdata on Mexican immigration to the United States (Fernandez-Huertas Moraga 2011; Kaestner and Malamud, 2014), which confirms modest if any selection from the source population when looking at those with especially low education. Analysis of workers with somewhat more education also shows little evidence of selection, as further discussed in the Data Appendix. See also the further discussion of immigration among skilled workers in Section II.D.

A. 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, Summers, and Aten 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. These data 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 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 the efficiency-units measure, $\tilde{H}$, as $success_T$. 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 Λ.

[Insert Table 1 about here.]

B. Traditional Accounting

Table 1 Panel A summarizes standard data for development accounting. 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 account for 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 in accounting for income differences.[8]

C. Generalized Accounting

Table 1 Panel B further summarizes additional data relevant to the generalized accounting. While the variation in unskilled labor equivalents, $\tilde{L}_1^R/\tilde{L}_1^P$, is modest in Table 1, the variation in unskilled labor itself can be large. For example, individuals with no education appear at approximately 1/5th the rate in Israel as they do in Kenya, and individuals with at least some college education appear at 34 times the rate in Israel as they do in Kenya. Table 1 presents additional comparisons between S. Korea and India and between the U.S. and Congo. Figure 2 presents labor allocation data for the full set of countries. In the presence of aggregators that feature scarcity or complementarities, these large differences in labor allocations can be felt strongly.

[Insert Figure 2 about here.]

One Parameter Example

We first examine the single parameter model of (6). Unskilled workers are grouped as those with completed primary education or less, which allows the skilled aggregator $Z(.)$ to encompass flexibly many higher-skilled categories. Table 2 (Panel A) reports the results of such a generalized accounting, focusing on the Israel-Kenya example as an illustrative case. 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, Λ_{GDL}, and the third row presents

[8] 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.

the resulting *success* measure for capital inputs in accounting for cross-country income differences.

[Insert Table 2 about here.]

As shown in the table, factor-based explanations for income differences are substantially amplified by allowing for differentiated labor compared to the traditional case. 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 $H^R/H^P = 10.5$.

Considering 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), we see similar large amplifications of human capital variation.[9] Calculating the elasticity of substitution, ε, at which capital inputs can fully account for income differences shows that the mean value is $\varepsilon = 1.55$ in this sample with a standard deviation of 0.34.

Table 2 (Panel B) further relaxes Assumption 4 and estimates h_1^R/h_1^P from immigrant and native worker wage data. Examining 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, mean wages are about 17% lower for these unskilled 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 Data Appendix for details).[10] 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.

Human capital stock estimations are presented for the broader sample in Figure 3. The ratio of human stocks is shown for each pair of countries from the 70/30 income percentile

[9] The Malaysia/Honduras income ratio is 3.8. As income ratios (and capital measures) converge towards 1, estimates of ε become noisier.

[10] This analysis makes wage comparisons among those with primary schooling or less, which is the relevant approach for the delination between worker groups in this accounting implementation. Similar wage corrections emerge when considering workers with somewhat more education, as discussed in the Data Appendix. More generally, Table 2 suggests that much more action comes from relaxing the perfect substitutes assumption, which is the focus of the analysis.

to the 99/1 income percentile. 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.

[Insert Figure 3 about here.]

Two Parameter Example

In practice, grouping those with completed primary or less education encompasses those with (i) completed primary education, (ii) some primary education, and (iii) no education in the Barro-Lee data. To the extent that such workers may be substantially different in practice (for example, those with completed primary education may be substantially more literate and numerate than those with no education and thus engage in different tasks) one may want to additionally consider more flexible aggregation across these subtypes. A two parameter model can then be estimated, as in (8), where μ additionally allows for non-perfect-substitutes aggregation among lower skill workers.

Figure 4 (upper row) summarizes accounting results for the completed primary school delineation when considering estimation across (ε, μ) space. The left panel presents the mean amplification Λ in human capital differences across the rich-poor country pairs in the sample. The right panel shows the mean *success* value across the rich-poor country pairs. The generalized accounting again shows that human capital variation and the level of *success* can be substantially elevated. Human capital differences increase as either ε or μ falls – i.e. as the estimation moves away from perfect substitutes. As imperfect substitutability is introduced among the unskilled, the *success* measure reaches 100% at higher levels of ε.

In practice, with seven educational attainment levels defined in the Barro-Lee data, one can consider numerous ways to delineate higher skilled and lower skilled workers in the accounting implementation. Online Appendix I (Figures A1.1-A1.6) extensively explores alternative definitions of the unskilled, including (i) all possible thresholds between skilled and unskilled in the Barro-Lee data and (ii) flexible aggregation among the unskilled themselves. Here we feature two additional cases: grouping lower-skilled workers as those with (a) some secondary or less education or (b) completed secondary or less education. Naturally, as more of the seven Barro-Lee educational attainment categories are grouped as lower-skill, the accounting becomes increasingly sensitive to how aggregation is performed among these lower-skilled workers.[11]

[Insert Figure 4 about here.]

Figure 4 further summarizes analysis based on these delineations, showing the mean amplification Λ in human capital differences and the mean *success* value across the rich-poor country pairs. For example, with $\varepsilon = 1.5$, one can now fully account for income differences with a mean value of $\mu = 4.9$ (middle row) and a mean value of $\mu = 3.5$ (lower row). As with the primary schooling case, we again see substantial amplification of human capital variation and substantial elevation of success across a range of parameters, with increased complementarities implying larger amplification.

Parameter Discussion

The theoretical analysis of Section I.C presented broad neoclassical conditions under which traditional accounting provides a lower bound on human capital variation across economies. The generalized accounting above suggests substantial amplification is possible, to the extent that capital variation may potentially be large enough to fully account for the large income variation across rich and poor countries.

Conclusive assessments of human capital variation depend partly on assessments of the appropriate aggregator. Micro-evidence analyzing the elasticity of substitution between skilled and unskilled labor typically suggests an elasticity in the $[1, 2]$ interval with common estimates toward the center of this range.[12] Perhaps the best-identified estimate is Ciccone and Peri (2005), who use compulsory schooling laws as a source of plausibly exogenous variation in schooling across U.S. states and conclude that $\varepsilon \approx 1.5$. These authors grouped more educated workers as those with completed secondary education or above, which corresponds most closely to the middle row of Figure 4. Using such an elasticity in the generalized accounting would imply large amplifications of human capital variation.

[11] Shifting all worker types into the "lower skilled" category and aggregating them as perfect substitutes would of course return the accounting to the traditional case.

[12] See, e.g. reviews in Katz and Autor (1999) and Ciccone and Peri (2005).

However, micro-evidence on the elasticity of substitution may apply poorly here for two reasons. First, the main mass of research in the labor literature delineates workers as college versus high-school educated (Ciccone and Peri (2005) is an exception) and more generally does not allow for flexible aggregation within the skilled or unskilled groups. Second, the microdata used in this literature comes from advanced economies and may not apply across the larger labor-allocation differences in the cross-country data.

The elasticity of substitution between worker types is traditionally inferred via OLS regression (Katz and Autor (1999)) and regression can also be applied in the generalized accounting context above. Such regressions demand substantial caveats given the identification challenges, which include the potential for endogenous relationships between observed and unobserved variables, measurement error, and multicollinearity problems. With such important caveats in mind, illustrative regressions are presented for the interested reader in Online Appendix I. Resulting estimates for ε and μ suggest that human capital differences across countries could be substantially amplified, such that the *success* measure approaches 100%. However, the identification challenges of such analysis, and their sensitivity, call for substantial skepticism about such regression estimates, as discussed further in Online Appendix I.

D. Discussion

This section considers intuitions and interpretations for the results and highlights open issues. We draw out further reasoning that comes with differentiated labor services as compared to the perfect substitutes case.

Wages and Output with Differentiated Labor Services

To develop additional intuition for the accounting results, it is useful to first consider the distinction between wages and outputs that emerges when moving away from the perfect-substitutes approach. 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 across labor types, turns off relative price differences for different workers. Thus, it equates wage returns with skill returns. By contrast, the generalized accounting allows for relative price differences for differentiated labor services (see (3)). In short, the generalized approach introduces downward sloping demand.

To the extent that rich countries "flood the market" with skilled labor compared to unskilled labor, downward sloping demand implies that the relative price of skilled services will decline. The more downward sloping the demand for skilled services, the greater the relative price decline and hence the greater the *output* return to schooling in rich countries needed to maintain the observed *wage* returns to schooling.[13] This provides further intuition for the generalized accounting. For example, as ε decreases in Table 2, demand becomes increasingly downward sloping. One correspondingly sees larger estimated differences in human capital services across countries. Online Appendix II provides specific estimates of variation in skilled service outputs that are implied by accounting exercise, given the wage and labor allocation data.

Immigration Outcomes with Differentiated Labor Services

Within each economy, the wage returns, labor allocations, and estimated labor productivities are consistent in the accounting by construction. One may also ask what to expect when moving workers across economies - i.e. via migration. With differentiated labor services, subtler issues arise than in the perfect substitutes case, because workers may now productively shift occupations when they enter a new economic environment. Broad intuition comes from comparative advantage applied to multiple tasks, where workers can shift their task allocation depending on relevant prices in the relevant economy. For example, if skilled workers in poor countries have very low quality in skilled services compared to skilled workers in rich countries, these skilled immigrants may undertake lower-skilled tasks. A concrete example is an immigrant engineer who drives a taxi. In practice, skilled immigrants to the US exhibit (1) occupational shifting into jobs that are typically performed by those with less education and (2) wage penalties compared to U.S.-born skilled workers but wages commensurate with those of less-educated U.S. workers, as shown in a companion paper (Jones 2011). Jones (2011) develops a model that may explain these immigration features while informing cross-country income differences along the above lines.[14]

[13] This interpretation requires the elasticity of substitution between skilled and unskilled labor to be greater than one, as is consistent with external evidence. I maintain this assumption in the discussion.

[14] In particular, an immigrant engineer driving a taxi becomes a natural (equilibrium) task allocation when the immigrant's engineering skills are of substantially poorer quality than a US-trained engineer. With reallocation across tasks, the wage in the new economy reflects not the worker's source-country task at the new-country price, but the worker's new-country task at the new-country price. If low-skilled services are scarce in rich countries (so these services are priced relatively highly) while the immigrant has low quality skill at the skilled task (which is abundant and thus priced relatively cheaply in the rich country) the skilled immigrant can do better by downshifting on the occupational ladder upon migration. The capacity to

Heterogeneous Skill Returns with Differentiated Labor Services

The generalized accounting, like the traditional case, infers the productivity gains from human capital investment building from evidence on the wage returns to schooling. An additional interpretative question is to ask whether the wage gains associated with more schooling are in fact due to human capital investment as opposed to simply being associated with it. This identification challenge, if left unchecked, would undermine the basis for accounting (generalized or traditional), and it raises additional interpretative questions concerning the link between human capital investments and other features, such as skill-biased technology residuals.

One can narrow interpretations by considering the large IV literature on the returns to schooling, which is intended to make causative assessments of schooling investments. The IV literature suggests an extra year of schooling raises wages by approximately 10%, which has been shown in both rich and poor countries (see, e.g., the review by Card (2003)). This literature provides an empirical basis for going beyond the identification problem, so that the returns to schooling can be interpreted causatively as the treatment of schooling itself. Given such wage evidence, what the generalized accounting effectively does, by considering differentiated labor services, is to add downward sloping demand to the interpretation of those IV wage returns.

Of course, the interesting additional implication is that one also interprets much greater impact of schooling on output in rich countries than in poor countries. In rich countries, a 10% gain in wages requires a relatively large increase in output, given the abundant 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 skilled outputs, given the relative scarcity of skilled workers. Bringing the generalized accounting together with the IV literature thus suggests two points: (1) human capital investment appears causative but (2) its effects are highly heterogeneous.

Such heterogeneous treatment effects suggest substantial care in assessing human capital policy. While policy statements go beyond the purpose of this paper, the following thought

reallocate thus helps the immigrant achieve a higher real wage than they otherwise would, and the marginal revenue product at the lower skilled tasks (e.g. retail services, taxi services, etc) provides a lower bound on the wage the immigrant can earn. This wage can also be substantially higher than the skilled wage the skilled worker leaves behind, if that worker comes from a poor country. See Jones (2011) for theory and evidence.

experiment may be clarifying. Given the generalized accounting, it would appear that reducing human capital stocks in the U.S. to the levels in the Congo (which would require taking virtually all college-educated workers and most secondary-educated workers throughout all sectors of the economy and replacing them with workers who have no education at all) would cause the U.S. to experience a precipitous drop in output. This outcome is very different than what traditional accounting allows. However, giving workers in the Congo the U.S. distribution of educational duration (coupled with appropriate physical capital deepening) does not necessarily imply that Congolese real income would rise to U.S. levels. In fact, fixing the current quality of skilled workers in the Congo, producing more such workers might be counterproductive. Thus, even as the generalized accounting may bring human capital toward the center of the development picture, simply increasing the quantity of education in poor countries may not be a well motivated implication. Heterogeneous treatment effects suggest that education policy choices require more subtle understanding, where the quality of investment may be key and where the success of educational investments may interact with other economic and institutional features.[15]

III. Conclusion

Human capital accounting operates under the assumption that the productivity advantage of human capital 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, accounting for no more than a small portion of the differences in per-capita income across countries. This influential conclusion suggests that human capital investments can play at most a modest role in economic development.

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

[15] Online Appendix II further explores labor differentiation among skilled workers, linking human capital investment, ideas, and institutions to provide a candidate explanation for large quality differences of skill workers across economies that can match the accounting findings.

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 cannot reveal themselves through relative wages alone unless 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 possibly account for the large income differences across countries.

The theoretical results in this paper provide broad conditions under which traditional human capital measurement, by ignoring complementarities and scarcity among human capital types, would understate human capital variation, suggesting important areas for further research, including a refined understanding of the sources of human capital quality. While the framework is illustrated here using 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, as do firm-level productivity studies. The urban economics and agglomeration literatures are another direction, where productivity gains from labor differentiation are often suggested but will not be captured using traditional human capital measures.

Appendix

Proof of Lemma 1

Proof. $H = G(H_1, H_2, ..., H_N)$ 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 $H = V(H_1, Z(H_2, ..., H_N)) = V(H_1, P(H, H_1))$, then we have from Lemma 1 $H = V_1(H_1, P(H, H_1))\tilde{H}$. This provides an implicit function determining H solely as a function of H_1 and $\tilde{H}$; that is, without reference to $Z(H_2, ..., H_N)$. ■

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, Summers, and Aten 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 seven 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 2 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. 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 account for income differences at somewhat higher values of the elasticity of substitution between the higher and lower skill workers.

[Insert Figure A1 about here.]

Variation in the Quality of Unskilled Labor

Following the theoretical analysis in Section I.C, 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, Ruggles et al. (2010)). Unskilled workers are defined in the primary analysis 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 A2 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.

[Insert Figure A2 about here.]

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.

Alternatively, one may compare individuals with somewhat more education. For example, one may consider workers who have completed 10th grade (educ=4 in the pums data set), who represent a larger share of the U.S. workforce.[16] Using this educational group, the

[16] This comparison also relates more closely to the analysis of Ciccone and Peri (2005), who defined lower skilled workers as high school dropouts. Ciccone and Peri (2005) provide a better-identified estimate of the parameter ε, suggesting $\varepsilon = 1.5$, although their estimate is made in the U.S. context and may not apply in cross-country data.

wage correction continues to adjust h_1^R/h_1^P modestly, and similarly to the primary schooling case, with a range of 0.85 to 1.29 depending on the income quintile of the source country.

The 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 ($h_1^{R|P} \approx h_1^P$). Views on this issue can be drawn from a large existing literature on immigrant selection. 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; Ibarraran and Lubotsky 2007) and positive selection (e.g. Chiquiar and Hanson 2005; Brucker and Trubswetter 2007; Brucker and Defoort 2009, McKenzie, Gibson, and Stillman 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, Gibson, and Stillman 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 2014). 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 (2014).[17] Table A1 shows the results, examining the real earnings measures used in these studies and compar-

[17] See their papers for detailed description of the data and their earnings variables.

ing 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.

[Insert Table A1 about here.]

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 the perfect-substitutes assumption tend to be much greater.

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Table 1: Basic Data

		Measure	Rich v Poor: 99th / 1st Percentile (USA/Zaire)	Rich v Poor: 85th / 15th Percentile (Israel/Kenya)	Rich v Poor: 75th / 25th Percentile (S Korea/India)
Panel A: Traditional Accounting Measures					
		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
		Traditional Success	9%	25%	45%
Panel B: Relative Labor Allocations					
	Labor Ratios (Rich / Poor)	No Education	.02	.21	.23
	Labor Ratios (Rich / Poor)	Some or Completed Primary	.23	.78	1.71
	Labor Ratios (Rich / Poor)	Some or Completed High School	11.7	6.7	3.4
	Labor Ratios (Rich / Poor)	Some or Completed College	56.2	34.3	3.2

Income and capital stock measures are per worker. Relative labor allocations are the population percentage of a given educational type in the rich country as a ratio to the corresponding percentage for the poor country. Populations percentages are for those over age 25. Data sources and methods are further described in the text and appendix.

Table 2: Human Capital and Income: Generalized Accounting

	Elasticity of Substitution Between Unskilled Labor, H_1, and Skilled Aggregate, $Z(H_2,..,H_N)$						
	1	1.2	1.4	1.6	1.8	2.0	∞
Panel A: Relaxing Assumption 3							
H^R/H^P	∞	358	21.9	8.6	5.4	4.1	1.3
Λ	∞	269	16.4	6.5	4.0	3.1	1
Success	∞	1050%	163%	88%	64%	54%	25%
Panel B: Relaxing Assumptions 3 and 4							
H^R/H^P	∞	306	18.6	7.3	4.6	3.5	1.1
Λ	∞	269	16.4	6.5	4.0	3.1	1
Success	∞	950%	147%	79%	58%	48%	23%

This table compares Israel and Kenya, which represent the 85th and 15th percentile countries respectively ranked by income per worker. H^R/H^P is the ratio of human capital stocks. Λ 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.

Figure 1: Income per Worker and Mean Schooling Duration

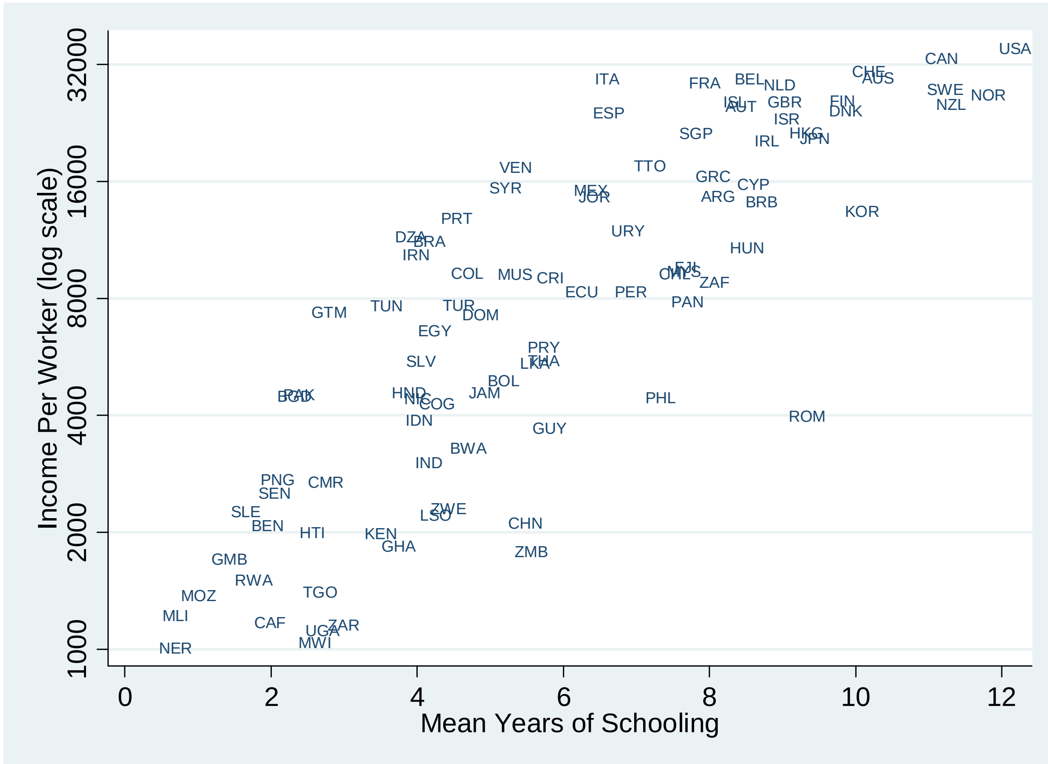
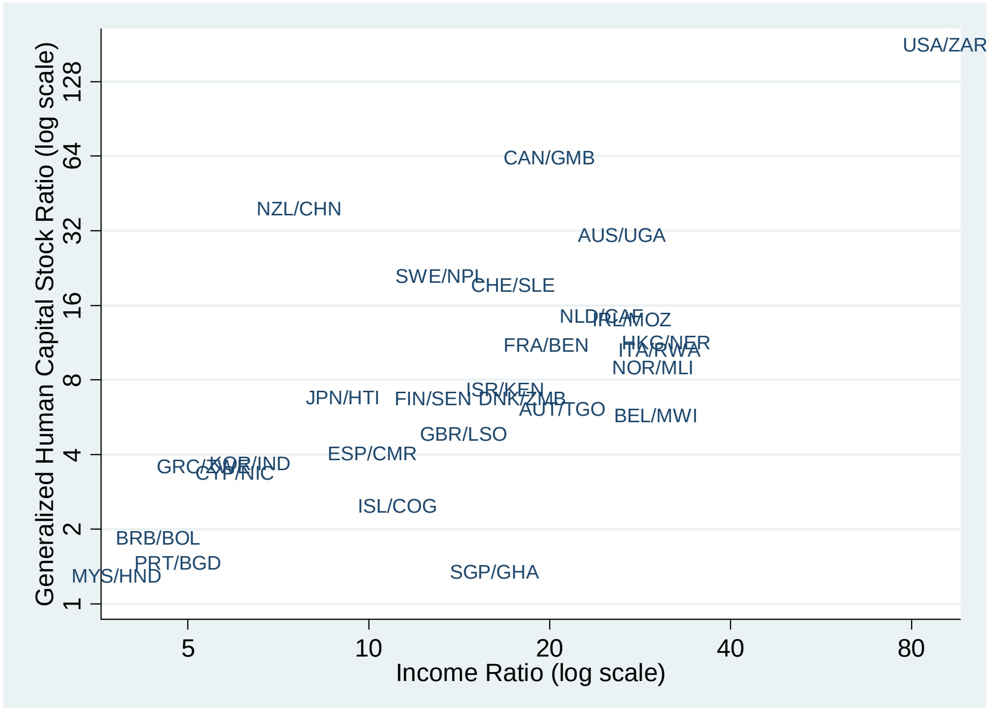


Figure 2: Fraction of Workers with Given Schooling

Figure 3: Human Capital Stock Variation

Panel A: Generalized Human Capital Stock



Panel B: Traditional Human Capital Stock

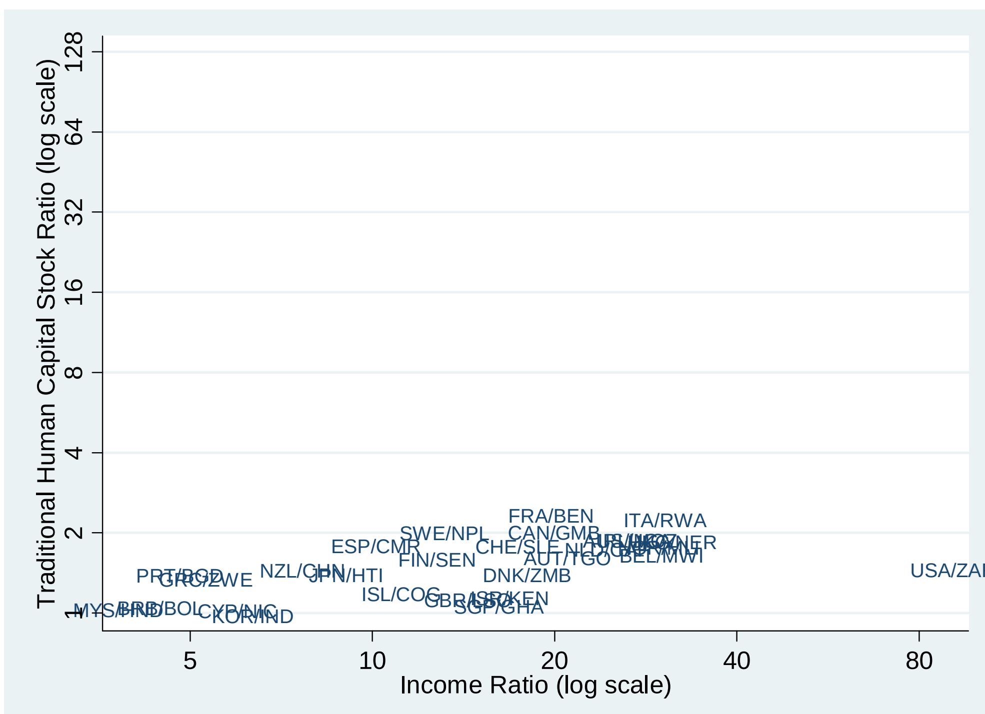
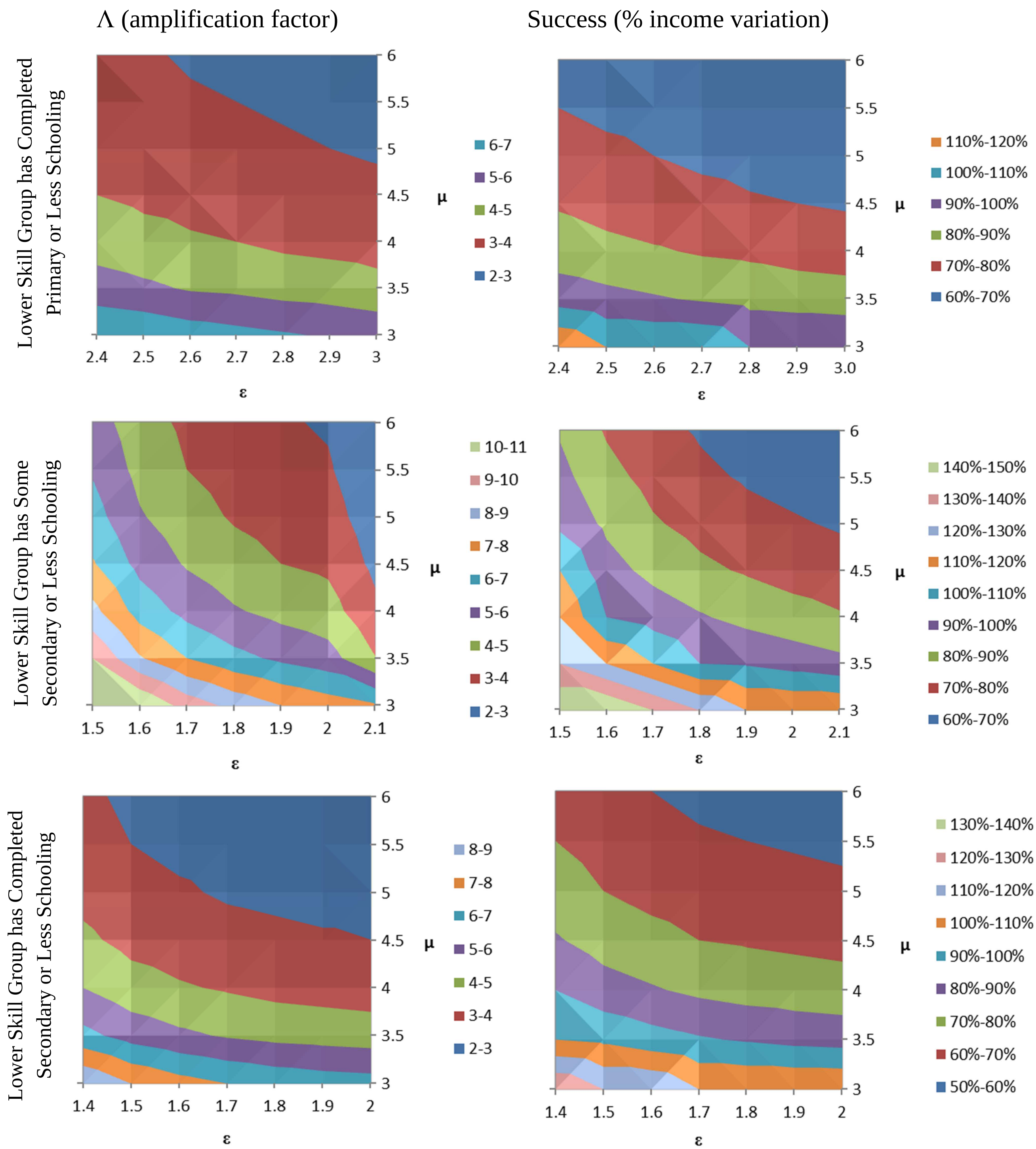


Figure 4: Generalized Accounting with Two Parameters



Notes: Generalized accounting is considered for different delineations between higher skill and lower skill groups. The lower skill group is alternatively defined as those with completed primary or less education (top row), some secondary or less education (middle row), and completed secondary or less education (bottom row). The amplification factor is the ratio of the generalized human capital differences to the traditional perfect-substitutes measure. Success is the percentage of cross-country income variation accounted for.

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

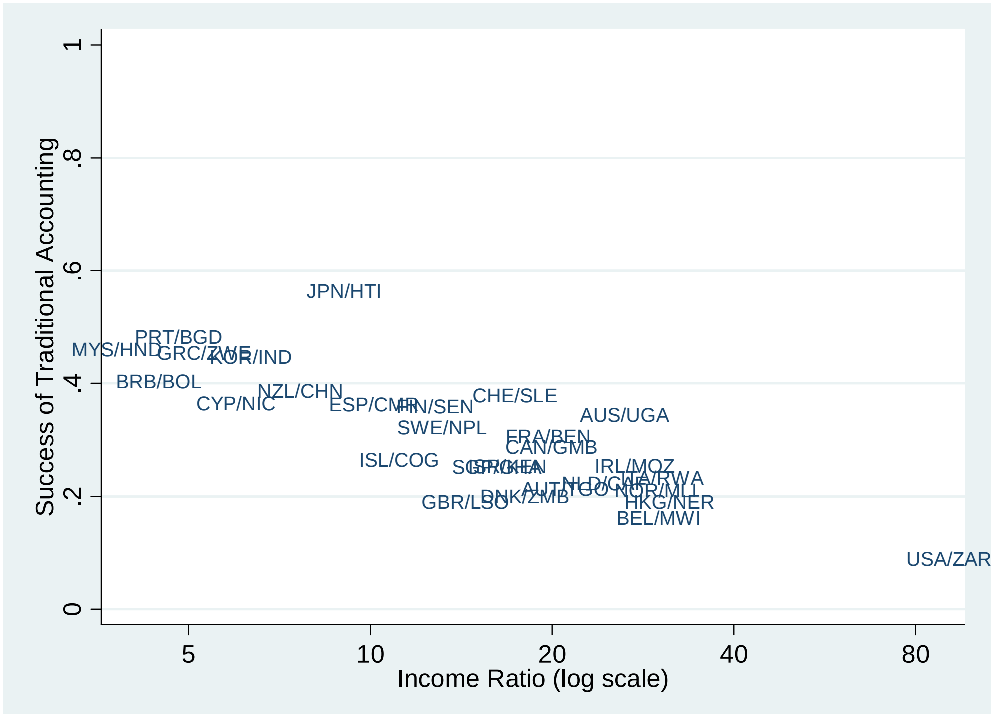


Figure A2: Wage Ratios from 2000 US Census among Employed Workers with Four or Less Years of Schooling, Conditional on Age and Gender

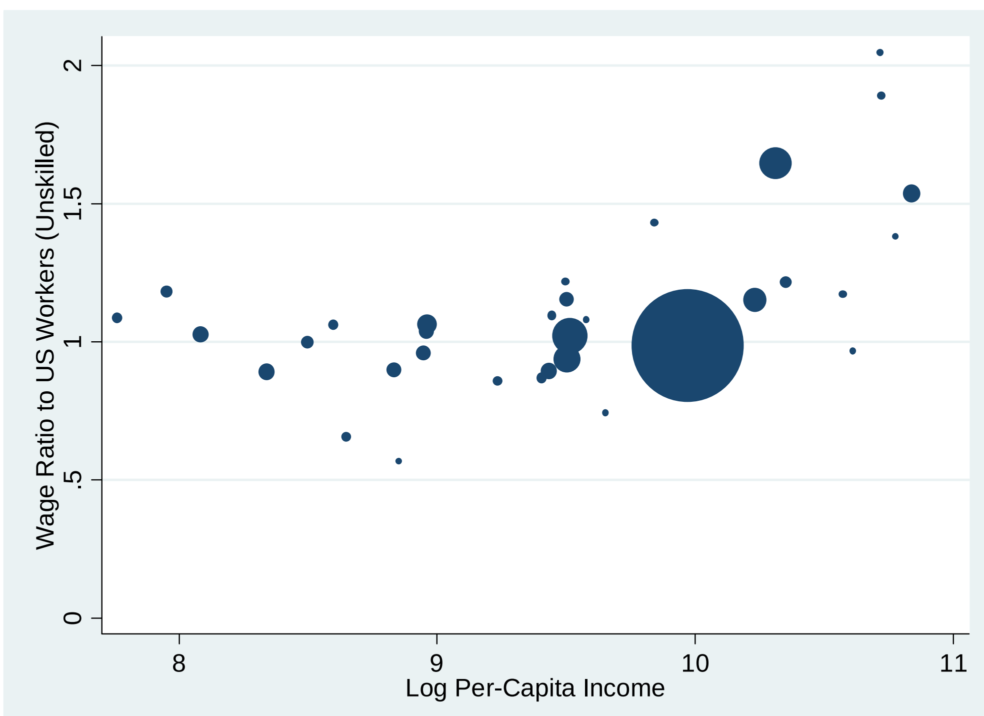


Table A1: Immigrant Selection, Four or Less Years of Schooling

	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
	(0.0290)	(0.0459)	(0.0325)	(0.0276)	(0.167)	(0.212)	(0.258)	(0.158)
Controls[(a)]	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:
[(a)]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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1 Online Appendix I: Further Human Capital Stock Analysis

This appendix presents additional calculations of human capital stocks. We further extend the estimations presented in the main text by considering all possible delineations between skilled and unskilled groups. We use the generalized, two-parameter human capital stock developed in the main text

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

where L_{11} is the mass of the least skilled category, h_{11} is their innate skill, $\tilde{L}_{11}$ is a perfect substitutes aggregation among the unskilled, and $\tilde{L}_1$ is the traditional perfect substitutes aggregation of all skill classes. Note that as $\mu \to \infty$ and $\varepsilon \to \infty$, we return to the standard perfect substitutes calculation used in traditional accounting.

To implement the accounting, we have

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

Related, recall the definition Λ from the main text, measuring the ratio of generalized human capital differences to the traditional perfect-substitutes calculation. The amplification of human capital differences is

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

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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 $success_T$ 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 Λ and *success* across countries given various (ε, μ) 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). Cases (3)-(5) were featured in the text but are repeated here for ease of comparison.

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 μ or ε falls – that is, as we move away from perfect substitutes. Third, higher cutoffs between skilled and unskilled workers produce a given success value at lower values of ε and/or μ. Put another way, as we expand the unskilled category, the success measure increasingly depends on μ. 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.

1.1 Regression Analysis

The generalized accounting elevates human capital differences across countries. However, the specific extent of this amplification depends on ε and μ. Defining unskilled workers as those with completed secondary or less schooling, the within-country micro-literature suggests $\varepsilon \in [1, 2]$. A relatively well-identified estimate suggests $\varepsilon \approx 1.5$ when comparing those with some secondary education (lower skill) to those with at least high school completion (higher skill) in U.S. data (Ciccone and Peri 2005). Estimates of ε for other categorizations of the unskilled and estimates of μ do not appear available, and the micro-literature estimates may not apply well in the cross-country context, where variation in labor allocation is substantially larger. Thus picking (ε, μ) definitively awaits further research. However, with very substantial identification caveats, one may also explore how simple regressions estimate these parameter values, following the traditional approach in the labor literature (e.g., see the review of Katz and Autor (1999)).

To write down the regression model, continue with the standard Cobb-Douglas production function, $Y = K^{\alpha}(AH)^{1-\alpha}$ and use the human capital aggregator generalized as in (1). Taking logs, the regression model becomes

$$\log Y^c = \beta_0 + \beta_1 \log \tilde{L}_1^c / L_{11}^c + \beta_2 \log \tilde{L}^c / \tilde{L}_1^c + \beta_3 \log H_{11}^c + \beta_4 \log K^c + u^c \tag{2}$$

where $\beta_1 = \frac{\mu(1-\alpha)}{\mu-1}$, $\beta_2 = \frac{\varepsilon(1-\alpha)}{\varepsilon-1}$, $\beta_3 = 1-\alpha$, $\beta_4 = \alpha$, and the error term encompasses the productivity residual, A.

Identification in this regression is extremely challenging for several reasons. First, the endogeneity of the variables, including potential correlations between the observed variables and unobserved variables in the residual term, can bias the coefficient estimates. Second, the regressors are all measured with error, possibly substantial error. Third, there is substantial collinearity between the right-hand side variables, which may be problematic given the relatively small sample. For all of these reasons, regression estimates must be viewed with extreme caution.

In practice, as shown in Table A1.1 (Panel A), running the full regression (2) does not produce meaningful results. Column 1 considers the case where unskilled workers have completed secondary education or less, but other delineations produce similar and equally difficult to interpret estimates. The coefficient on physical capital (β_4) implies a capital share (α) of approximately 0.69, while the coefficient β_3 provides a noisy estimate of α that is substantially greater than 1. These values of α are neither consistent with each other[1] nor consistent with well-known estimates of the capital share, which suggest that α is about 1/3 (e.g. Gollin 2002, Bernanke & Gurkaynak 2002). Moreover, the implied estimates of ε and μ are ambiguous because α is unclear.[2] The full regression model thus appears uninformative of actual parameter values. As shown in column 2, regressing of $\log K$ on the other explanatory variables produces an R^2 of 0.82, suggestive of collinearity problems (and the possibility of endogenous relationships between these variables). One way forward with such regressions, as often used with collinearity problems, is to assert the parameters we think are known from other literature. Namely, one may take the usual view that $\alpha = 1/3$, which implies the values of β_3 and β_4, and run the constrained regression.

With substantial caution given the identification challenges, these results are presented in Table A1.1 (Panel B). Each column considers a different delineation between skilled and unskilled workers, and the implied values for ε and μ are presented in the final rows. These specifications produce several observations. First, raising the threshold between unskilled and skilled workers produces lower estimates of ε. This finding would suggest that complementarities between skilled and unskilled workers appear greatest when we isolate the very highly skilled. Second, 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 similar to that literature's estimates. Third, the point estimates show a higher elasticity of substitution among unskilled workers, with $\hat{\mu} \approx 4$ being typical. This finding would suggest that unskilled workers are more substitutable among themselves than they are with skilled workers.

A slightly relaxed version of the constrained regression is presented in Table A1.1 (Panel C). Here we continue to constrain the role of physical capital, with $\beta_4 = 1/3$, but now let β_3 be estimated by the regression. As shown in the table, the estimates for ε and μ appear broadly similar with this additional flexibility as in the regressions of Panel B, and these regressions continue to estimate $\hat{\varepsilon} = 1.5$ using the completed secondary delineation. Interestingly, the estimates for β_3 are now statistically consistent with its theoretical condition ($\beta_3 = 1 - \alpha$), giving plausible values for the capital share.

[1] A formal test strongly rejects the restriction $\beta_3 + \beta_4 = 1$.

[2] These estimated parameters can be negative and thus also outside their theoretical constraints.

Lastly, and again with substantial caution required, Figure A1.7 takes the estimates of the ε and μ 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 would 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 related *success* measure ranges from 72% to 109%. Thus, across the possible delineations between skilled and unskilled workers, large amplifications of human capital differences would appear with, correspondingly, a capacity to account for 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 $Z(H_1, H_2, ..., H_N)$. At the same time, it is useful to look "underneath the hood" and gain a better understanding and intuition 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 the paper, 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. 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 candidate avenue for understanding the heterogeneous treatment effects of education across countries and draws a natural link between human capital, institutions, ideas, and skill-bias.

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

$$\frac{h_i}{h_j} = \frac{w_i}{w_j}\frac{G_j}{G_i} \tag{3}$$

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. In practice, skilled labor supply appears far higher in rich countries while wage returns appear rather similar across countries. Figure A2.1 presents these data. Defining lower skilled workers as those with completed primary or less education, wage return variation is tiny compared to labor supply variation. For example, the skilled labor allocation (L_Z/L_1) is 2300% greater in Israel compared to Kenya, while the mean wage returns (w_z/w_1) are only 20% lower. As another example, the skilled labor allocation is 17500% greater in the USA compared to Congo, while mean wage returns are only 15% lower. With downward sloping demand, and given these large differences in labor allocations yet similar wage returns, skilled workers in rich countries will therefore appear far more productive (in units of output) than skilled workers in poor countries.

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

$$\frac{h_z^R/h_1^R}{h_z^P/h_1^P} = \left(\frac{w_z^R/w_1^R}{w_z^P/w_1^P}\right)^{\frac{\varepsilon}{\varepsilon-1}} \left(\frac{L_z^R/L_1^R}{L_z^P/L_1^P}\right)^{\frac{1}{\varepsilon-1}} \tag{4}$$

where $h_z = Z(H_2, H_3..., H_N)/L_Z$ is the mean flow of services from skilled workers. That is, the left hand side tells us the output gains from schooling in rich versus poor countries that are implied by the generalized accounting. These are the output gains that are consistent by construction, with the wage returns data, the labor allocation data, and the elasticity of substitution parameter.

Table A2.1 (Panel A) reports the implied variation in h_z/h_1 for various values of the parameter ε, continuing with the rich-poor example in Table 2 of the main text. Recall that human capital stock variation eliminates residual total factor productivity variation when $\varepsilon \approx 1.6$. At this value of ε, 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, $Z(H_2, H_3..., H_N)$. 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

$$Z = \left[\sum_{i=2}^{N} H_i^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}} \tag{5}$$

where η 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.[3] 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 A2.1 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.

2.1.1 Further Intuition from Equilibrium Reasoning

To further interpret these findings, it is useful to consider why the world looks like Figure A2.1, where there is little variation in wage returns across countries yet massive variation in labor allocations. One straightforward interpretation lies in endogenous labor supply. Simple endogenous labor supply models act to drive individuals' equilibrium wage returns toward their discount rates (e.g. Willis 1986) as workers optimize their human capital investments. Namely, if wage returns to schooling were unusually high, then more individuals would choose to become skilled, causing the relative prices of skilled services to fall and constraining wage gains. Thus endogenous labor supply can act to decouple equilibrium wage returns from productivity considerations, and 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.

To see this idea formally, 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 θ 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

$$\frac{\partial w/\partial s}{w} = r \tag{6}$$

[3] The returns for the sub-groups of workers are calculated using (5) 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 ε where capital variation fully explains the income variation.

In other words, the individual's wage return will be log-linear in educational duration at their optimal schooling choice, with a return of $r\%$.[4] 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 (6) 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 (6) 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 A2.1, 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.

2.2 The Division of Labor

In advanced economies, and especially among the highly educated, skills appear highly differentiated. Skills appear to differ across medical doctors, chemical engineers, computer scientists, molecular biologists, lawyers, and architects, and skills within professions can appear highly differentiated themselves (e.g. among medical doctors). 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).

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 $Z(.)$.

[4] 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).

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 2011), 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 may 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 2011). 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 (2011), 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.[5]

Next consider the choice of s and n that maximizes the discounted value of skilled services per-capita.[6] 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 θ captures the degree of coordination costs that ensue with greater labor division. Let $f(ns) = \alpha(ns)^\beta$, where α and β are educational technology parameters. It follows from the above maximization problem that[7]

$$s^* = \beta/r \tag{7}$$

$$n^* = \beta/\theta \tag{8}$$

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 (θ), which limit specialization.

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

$$\frac{h^R}{h^P} = \frac{\alpha^R}{\alpha^P}\left(\frac{r^P\theta^P}{r^R\theta^R}\right)^\beta \tag{9}$$

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

[5] For analytical convenience, we will let team size, n, be a continuous variable.

[6] 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 2011). Here we consider the output maximizing case as a useful benchmark.

[7] The following stationary points are unique, and it is straightforward to show that they satisfy the conditions for a maximum.

2.2.3 Calibration Illustration

We focus on the division of labor. Note from (8) that with common β the equilibrium difference in the division of labor (that is, the team size ratio) is equivalent to the inverse coordination cost ratio, θ^P/θ^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 A2.2 then plots the implied variation in the division of labor, n^R/n^P, that reconciles (9) with the quality variation h_z^R/h_z^P implied by (4), 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 22-fold difference. These differences would fall to the extent that the education technology (α,β) is superior in richer countries.

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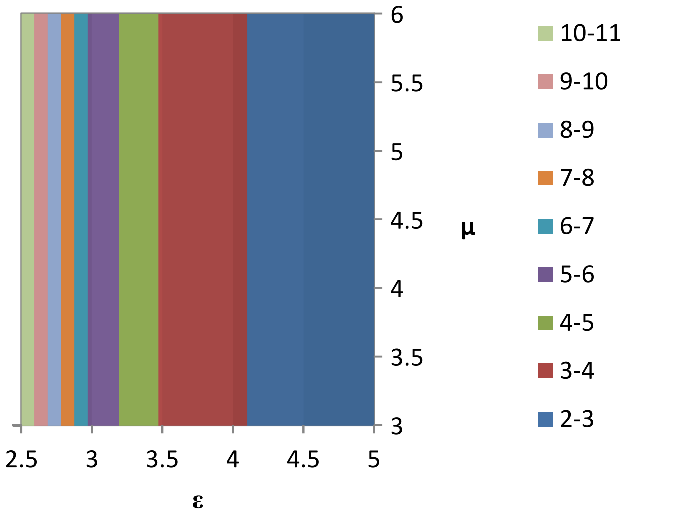
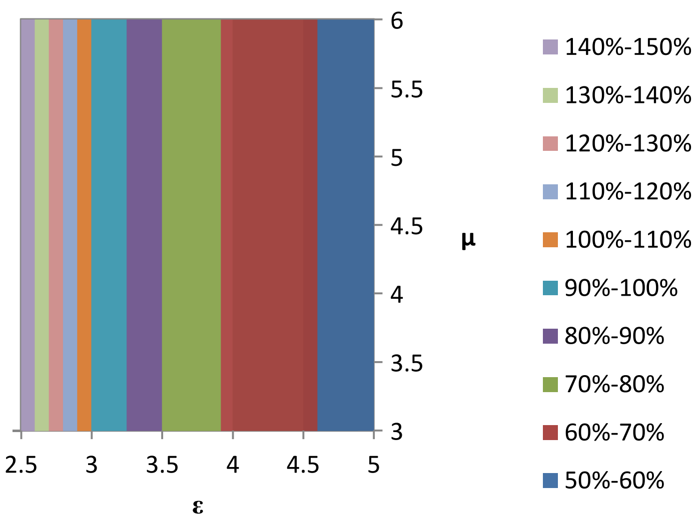
Figure A1.1: Generalized Accounting, Unskilled Have No Education

Λ (Amplification of human capital differences)



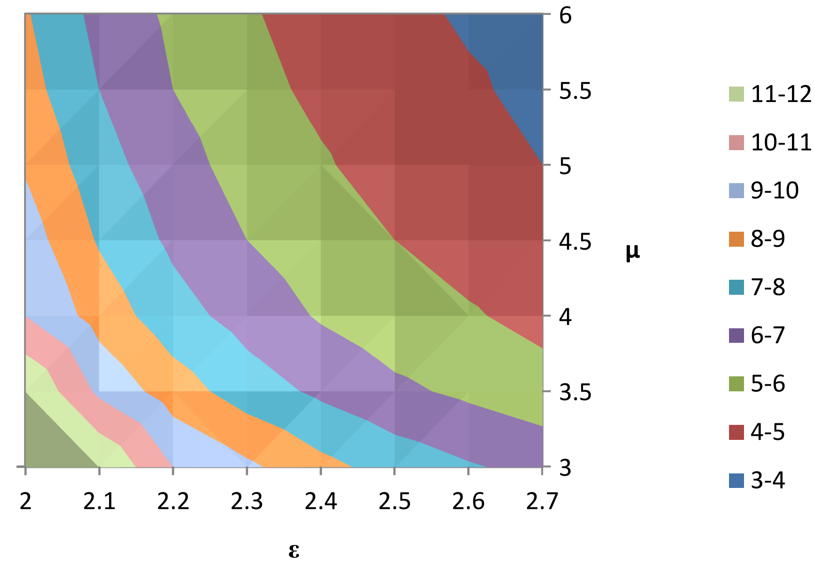
Success (Percentage of income variation explained)



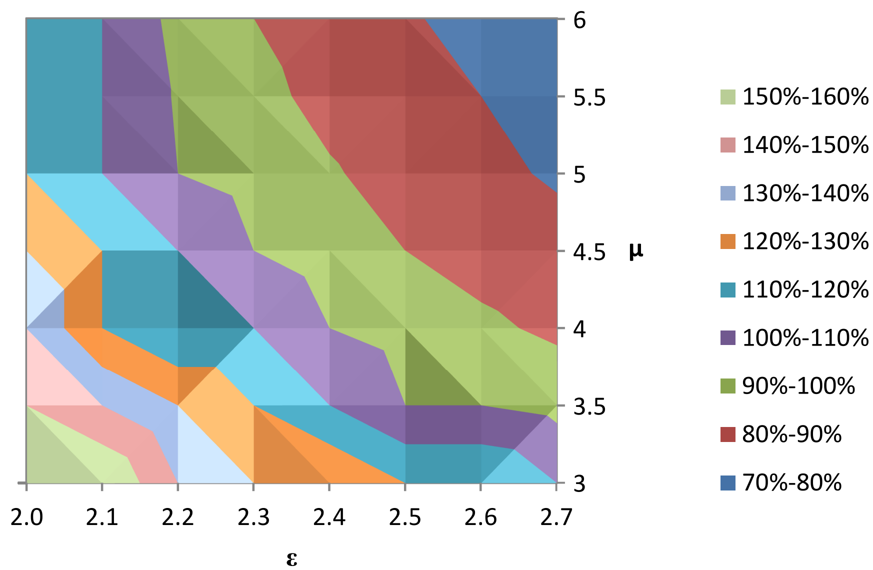
Notes: The upper panel presents the measure Λ, which is the ratio of the generalized human capital differences to traditional human capital differences. The lower panel presents the measure "success", which is the percentage of the income variation explained by capital input variation. In both panels, at a given ε and μ, 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 μ plays no role.

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

Λ (Amplification of human capital differences)



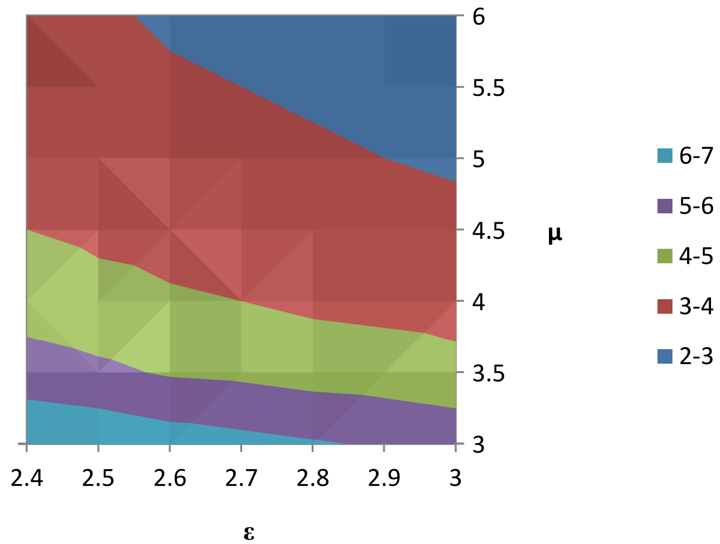
Success (Percentage of income variation explained)



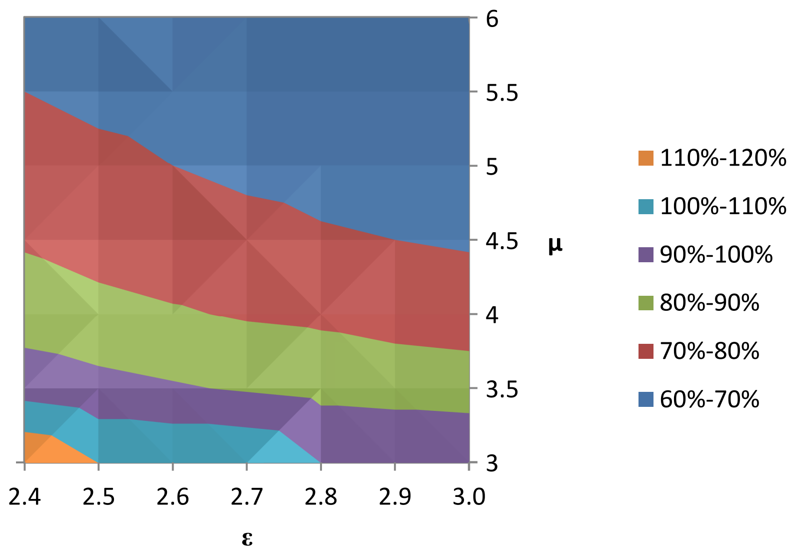
Notes: The upper panel presents the measure Λ, which is the ratio of the generalized human capital differences to traditional human capital differences. The lower panel presents the measure "success", which is the percentage of the income variation explained by capital input variation. In both panels, at a given ε and μ, 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

Λ (Amplification of human capital differences)



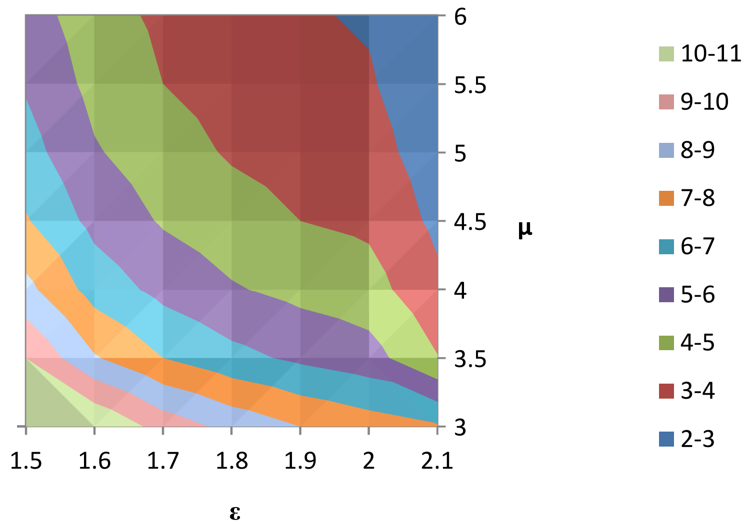
Success (Percentage of income variation explained)



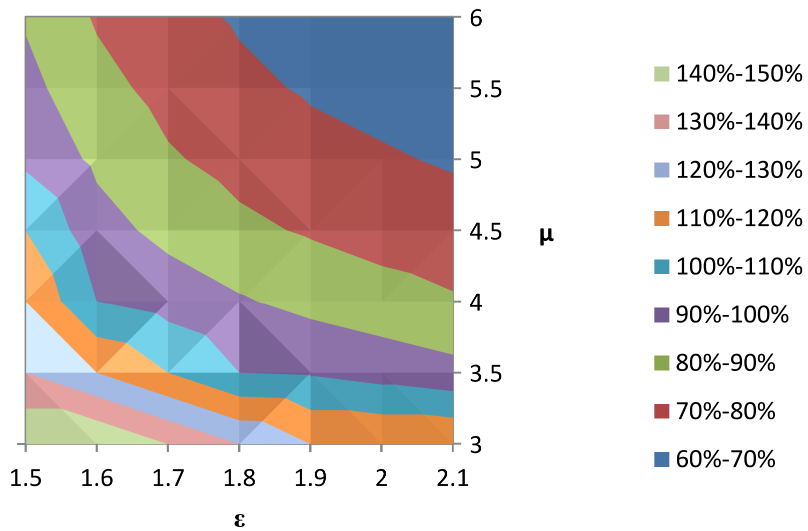
Notes: The upper panel presents the measure Λ, which is the ratio of the generalized human capital differences to traditional human capital differences. The lower panel presents the measure "success", which is the percentage of the income variation explained by capital input variation. In both panels, at a given ε and μ, 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

Λ (Amplification of human capital differences)



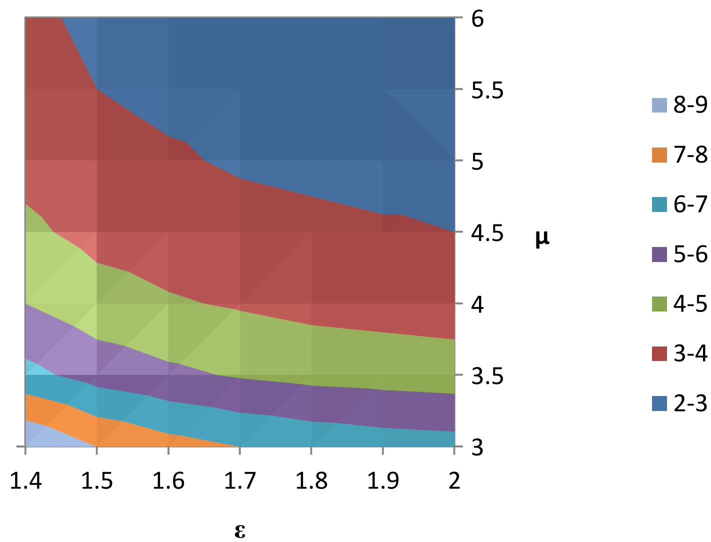
Success (Percentage of income variation explained)



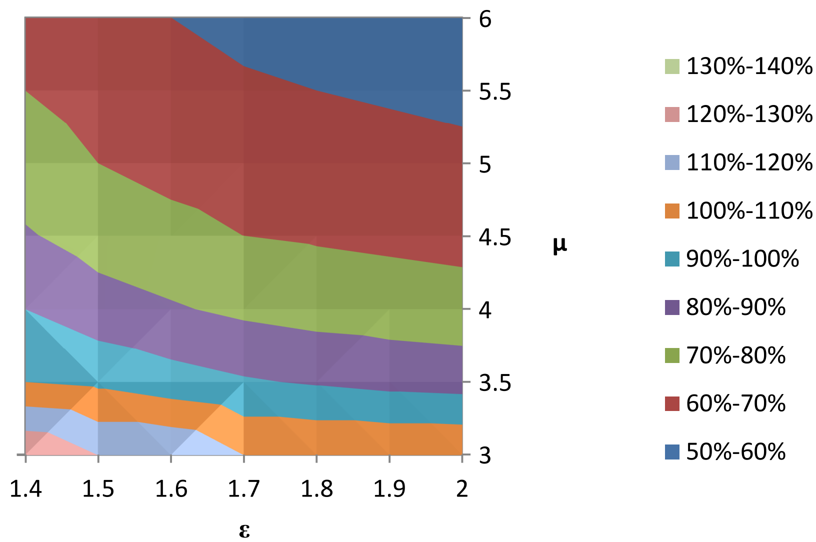
Notes: The upper panel presents the measure Λ, which is the ratio of the generalized human capital differences to traditional human capital differences. The lower panel presents the measure "success", which is the percentage of the income variation explained by capital input variation. In both panels, at a given ε and μ, 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

Λ (Amplification of human capital differences)



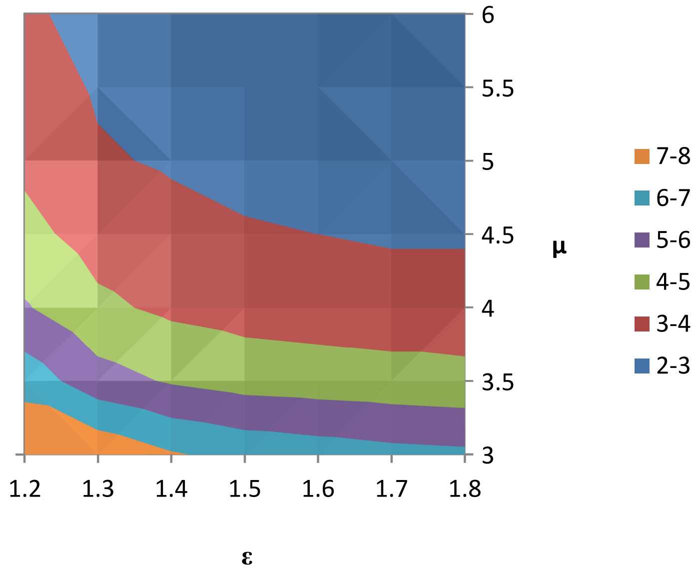
Success (Percentage of income variation explained)



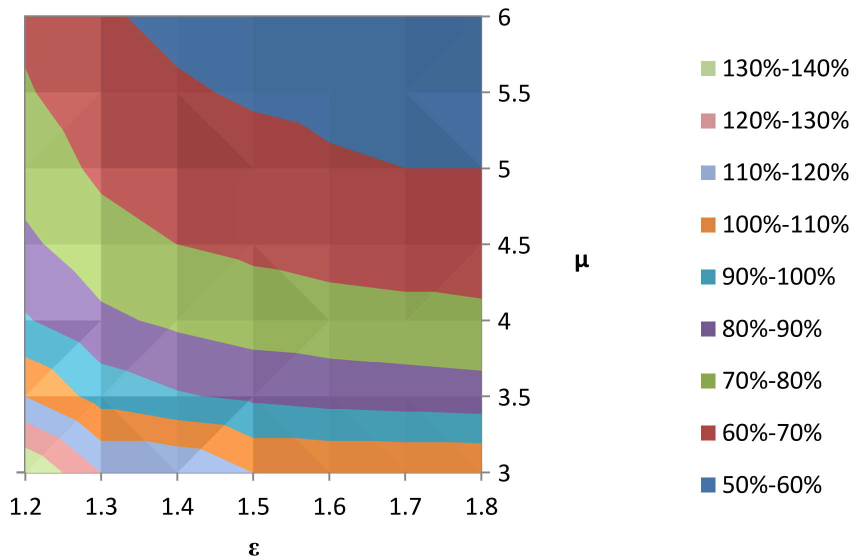
Notes: The upper panel presents the measure Λ, which is the ratio of the generalized human capital differences to traditional human capital differences. The lower panel presents the measure "success", which is the percentage of the income variation explained by capital input variation. In both panels, at a given ε and μ, 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

Λ (Amplification of human capital differences)

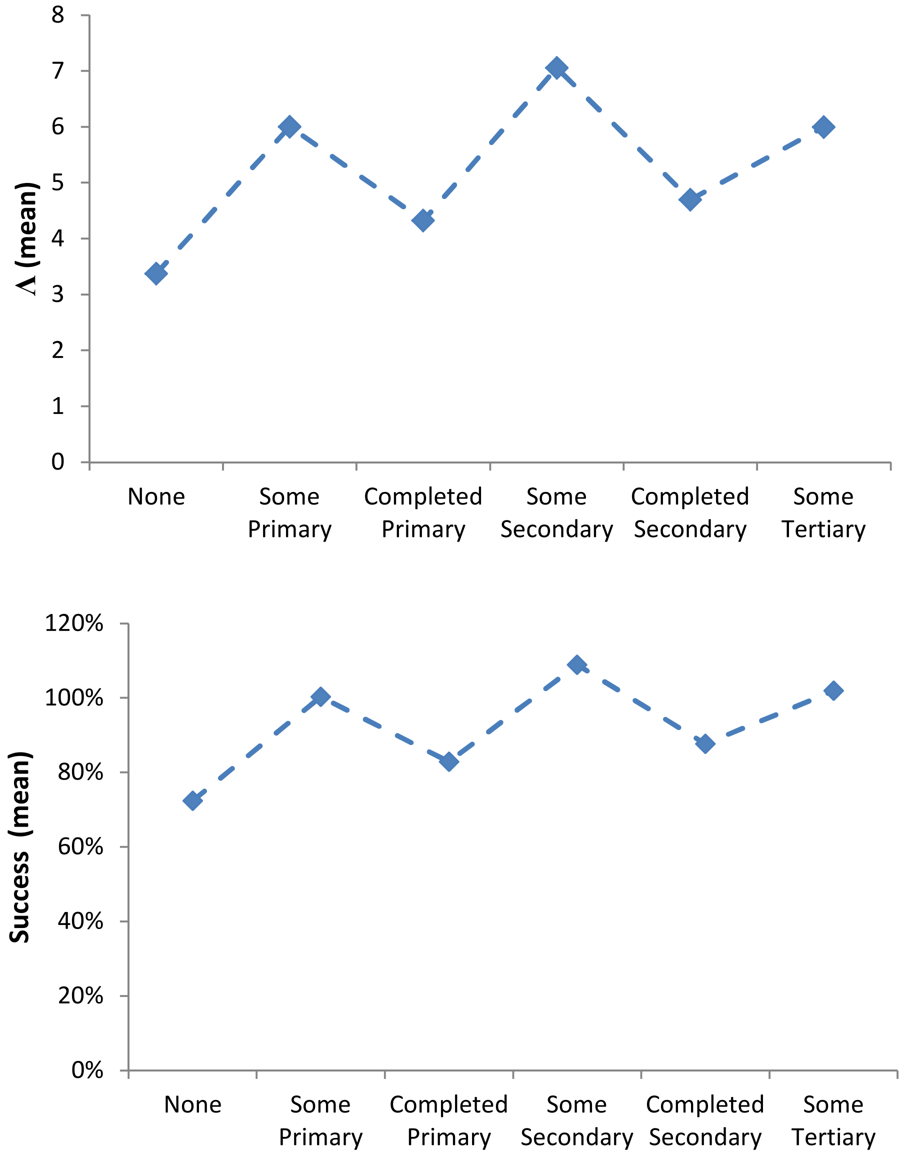


Success (Percentage of income variation explained)



Notes: The upper panel presents the measure Λ, 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 ε and μ, 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 ε and μ from the relevant column in Table A1.C. 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: Sources of Human Capital Variation: Labor Supply versus Wages

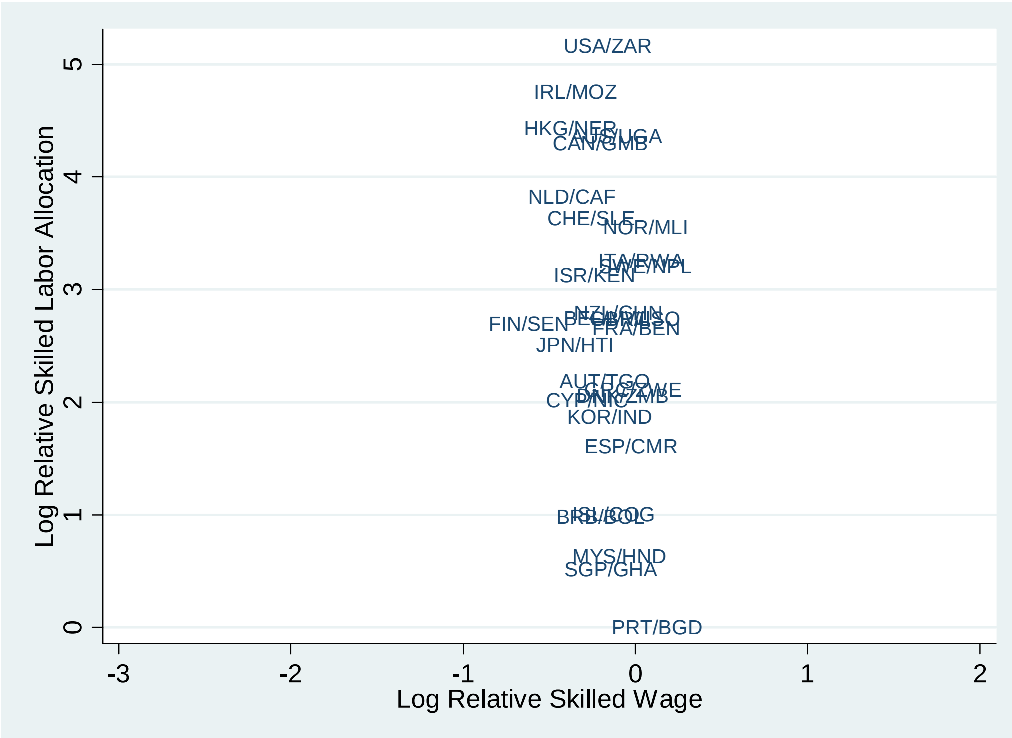


Figure A2.2: Calibrated Difference in Specialization across Countries

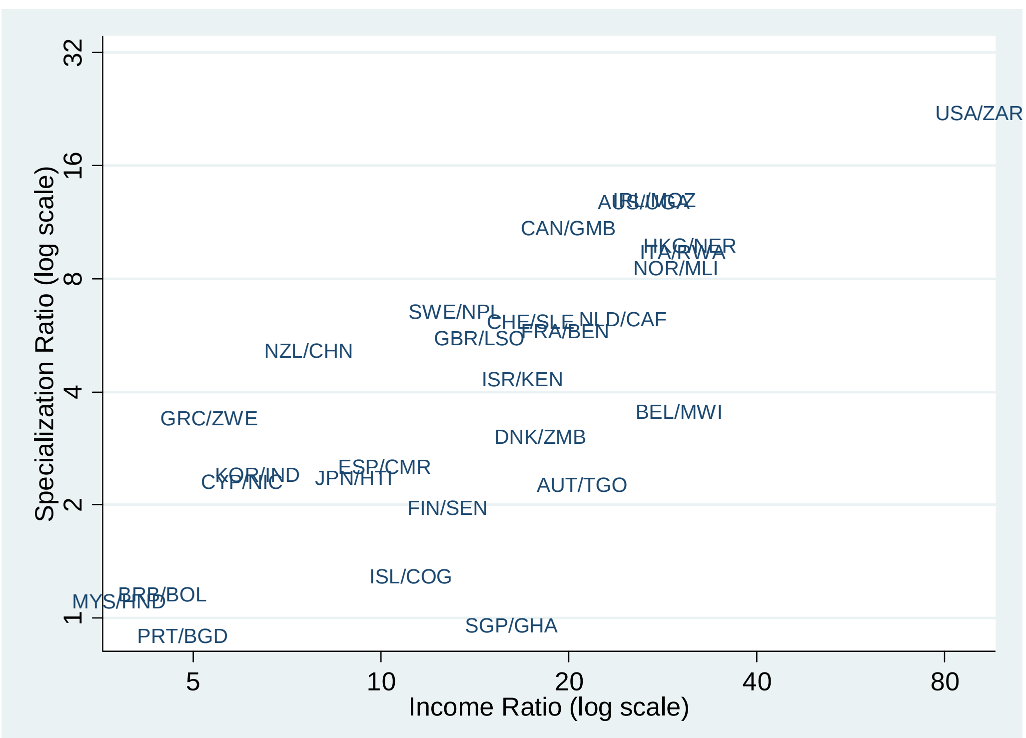


Table A1.1: Regression Estimates

Panel A: Regressions with Physical Capital

	(1)	(2)
	Dependent Variable	
	log(Y)	log(K)
$\log(\widetilde{H_1}/H_{11})$	0.228	4.844***
	(0.349)	(1.251)
$\log(\widetilde{H}/\widetilde{H_1})$	-0.294	3.311***
	(0.249)	(0.683)
$\log(H_{11})$	-0.333	2.779***
	(0.245)	(0.753)
$\log(K)$	0.687***	
	(0.0532)	
Observations	56	56
R-squared	0.966	0.817

Panel B: Regressions asserting α = 1/3 with $\beta_4 = 1 - \beta_3 = \alpha$

	(1) No Schooling	(2) Some Primary	(3) Completed Primary	(4) Some Secondary	(5) Completed Secondary	(6) Some Tertiary
$\log(\widetilde{H_1}/H_{11})$	0.949***	1.117***	1.113***	1.550***	1.946***	3.005***
	(0.0252)	(0.0875)	(0.116)	(0.259)	(0.547)	(0.891)
$\log(\widetilde{H}/\widetilde{H_1})$	--	0.823***	0.892***	0.859***	0.892***	0.894***
		(0.0503)	(0.0376)	(0.0385)	(0.0330)	(0.0308)
Observations	56	56	56	56	56	56
R-squared	0.948	0.953	0.950	0.954	0.951	0.951
Implied ε	3.36	2.48	2.49	1.76	1.52	1.29
	[3.01-3.87]	[2.07-3.41]	[1.99-4.10]	[1.48-2.81]	[1.28-4.45]	[1.16-2.17]
Implied μ	--	5.26	3.96	4.47	3.95	3.93
		[3.60-12.8]	[3.22-5.42]	[3.48-6.77]	[3.29-5.16]	[3.31-5.00]

Panel C: Regressions asserting α = 1/3 with $\beta_4 = \alpha$ only

	(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***	1.055***	1.117***	1.476***	1.939***	3.033***
	(0.258)	(0.244)	(0.262)	(0.309)	(0.547)	(0.927)
$\log(\widetilde{H}/\widetilde{H_1})$	0	0.753***	0.897***	0.757**	0.876***	0.816**
	(0)	(0.276)	(0.272)	(0.285)	(0.292)	(0.313)
$\log(H_{11})$	0.758**	0.592*	0.672**	0.557*	0.649*	0.582
	(0.305)	(0.300)	(0.310)	(0.315)	(0.327)	(0.350)
Observations	56	56	56	56	56	56
R-squared	0.732	0.756	0.742	0.760	0.743	0.747
Implied ε	3.79	2.28	2.51	1.61	1.50	1.24
	[1.97-∞]	[1.62-∞]	[1.7-∞]	[1.36-2.82]	[1.27-4.18]	[1.14-1.95]
Implied μ	--	4.66	3.99	3.77	3.85	3.48
		[1.83-]	[1.88-]	[1.73-]	[1.80-]	[1.68-]

Notes: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Panel A groups unskilled workers as those with completed secondary or less education. Other delineations show similar results. Delineations in Panels B and C are as indicated at top of each column. See text of Online Appendix I for discussion.

Table A2.1: Human Capital Services by Educational Groups

Panel A: Human capital services, grouping secondary and tertiary educated workers

	Elasticity of Substitution Between Unskilled Labor, H_1, and Skilled Aggregate, $Z(H_2,..,H_N)$					
	1	1.4	1.6	1.8	2	∞
$\frac{(h_Z / h_1)^R}{(h_Z / h_1)^P}$	∞	1101	98.6	29.5	14.3	0.79

Panel B: Human capital services, secondary and tertiary educated workers treated separately

	Elasticity of Substitution Between Secondary, H_2, and Tertiary, H_3, Human Capital Services					
	1.2	1.4	1.6	1.8	2	∞
$\frac{(h_2 / h_1)^R}{(h_2 / h_1)^P}$	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 85th and 15th 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.