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

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

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

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

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.

References

[1] Agrawal, Ajay, Avi Goldfarb, and Florenta Teodoridis. "Does Knowledge Accumulation Increase the Returns to Collaboration? Evidence from the Collapse of the Soviet Union," University of Toronto mimeo, 2013.

[2] Becker, Gary S. and Kevin M. Murphy. "The Division of Labor, Coordination Costs, and Knowledge", *Quarterly Journal of Economics*, November 1992, 107 (4), 1137-1160.

[3] Bernanke, Ben and Refet Gürkaynak, "Is Growth Exogenous? Taking Mankiw, Romer, and Weil Seriously," in: *NBER Macroeconomics Annual 2001*, 2002.

[4] Borjas, George J. and Kirk B. Doran. "The Specialization of Scientists," University of Notre Dame mimeo, 2011.

[5] Card, David. "Estimating the Return to Schooling: Progress on Some Persistent Econometric Problems," *Econometrica*, 69 (5), 2003, 1127-1160.

[6] Gollin, Douglas, "Getting Income Shares Right," *Journal of Political Economy*, 2002.

[7] Hanushek, Eric and Ludger Woessmann, "The Role of Cognitive Skills in Economic Development," Journal of Economic Literature, 46(3), 2008, 607-668,

[8] Heckman, James J., Lochner, Lance J., and Petra E. Todd. "Earnings Functions: Rates of Return and Treatment Effects: The Mincer Equation and Beyond", *Handbook of the Economics of Education Volume 1*, Chapter 7, 2006.

[9] Jones, Benjamin F. "The Burden of Knowledge and the Death of the Renaissance Man: Is Innovation Getting Harder?", *Review of Economic Studies*, January 2009.

[10] Jones, Benjamin F. "The Knowledge Trap: Human Capital and Development Reconsidered", NBER Working Paper #14138 and Northwestern University mimeo, 2011.

[11] Schoellman, Todd. "Education Quality and Development Accounting," *Review of Economic Studies*, 2012.

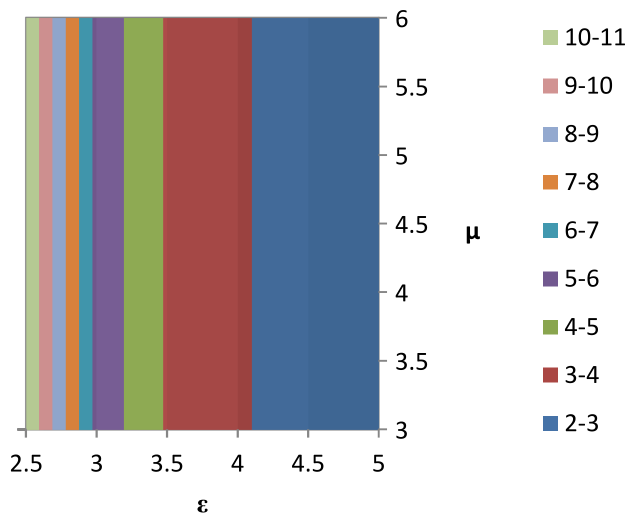
[12] Smith, Adam. *An Inquiry into the Nature and Causes of the Wealth of Nations*. 1776.

[13] Willis, Robert J. "Wage Determinants: A Survey and Reinterpretation of Human Capital Earnings Functions," *Handbook of Labor Economics Volume I*, Chapter 10, O. Ashenfelter and R. Layard (eds.), 1986.

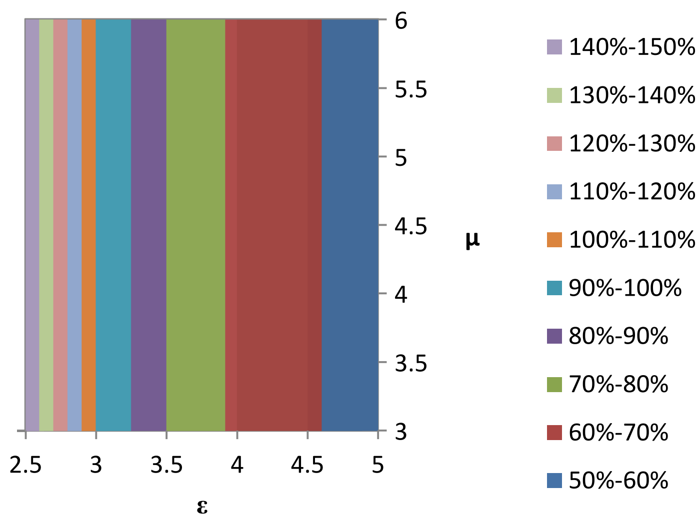
[14] Wuchty, Stefan, Benjamin F. Jones and Brian Uzzi. "The Increasing Dominance of Teams in the Production of Knowledge", *Science*, 2007, 318, 1036-39.

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

Λ (Amplification of human capital differences)



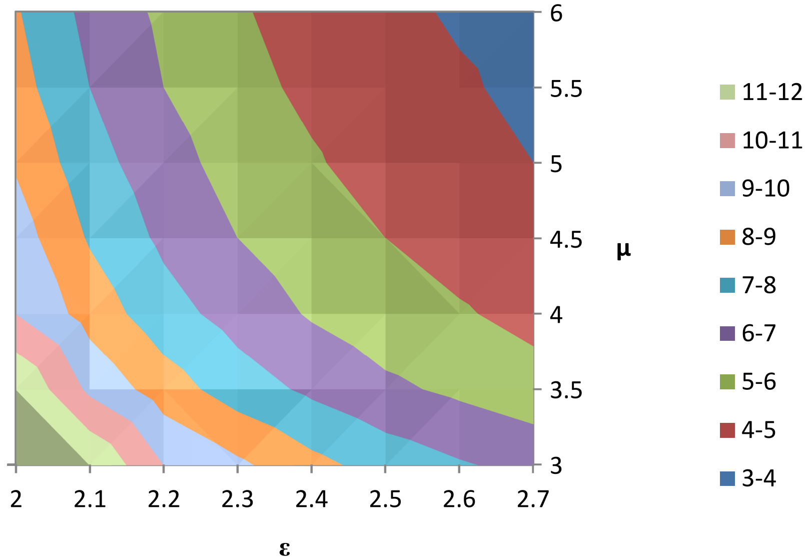
Success (Percentage of income variation explained)



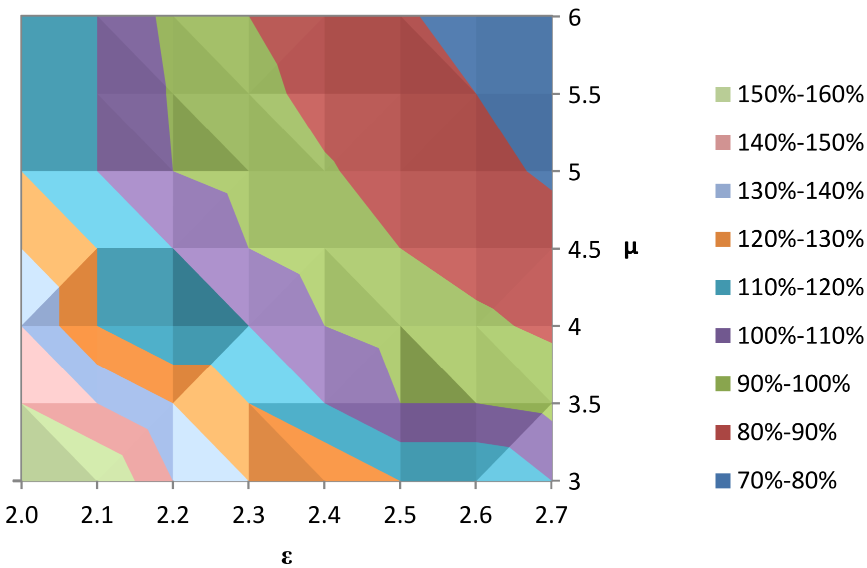
Notes: The upper panel presents the measure Λ, which is the ratio of the generalized human capital differences to traditional human capital differences. The lower panel presents the measure "success", which is the percentage of the income variation explained by capital input variation. In both panels,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



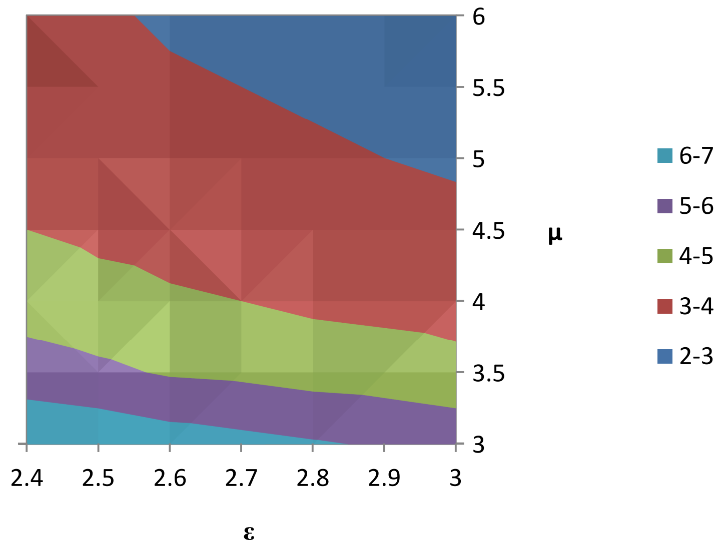
Success (Percentage of income variation explained)



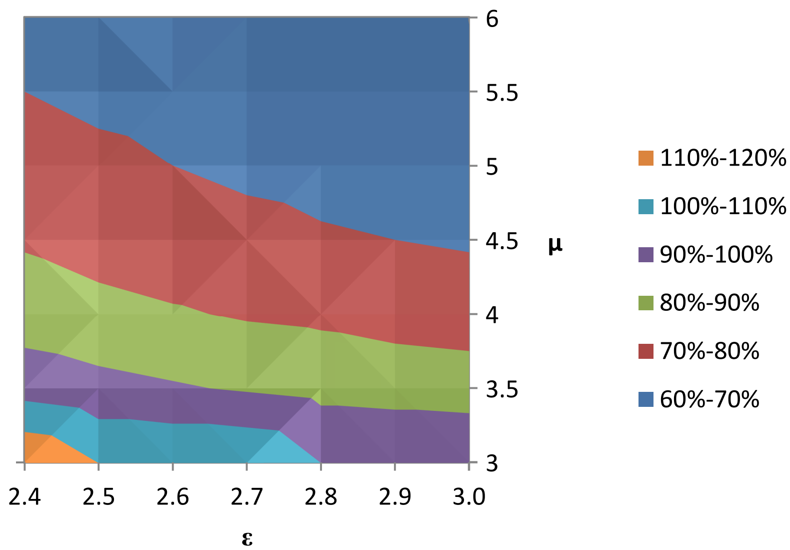
Notes: The upper panel presents the measure Λ, which is the ratio of the generalized human capital differences to traditional human capital differences. The lower panel presents the measure "success", which is the percentage of the income variation explained by capital input variation. In both panels,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



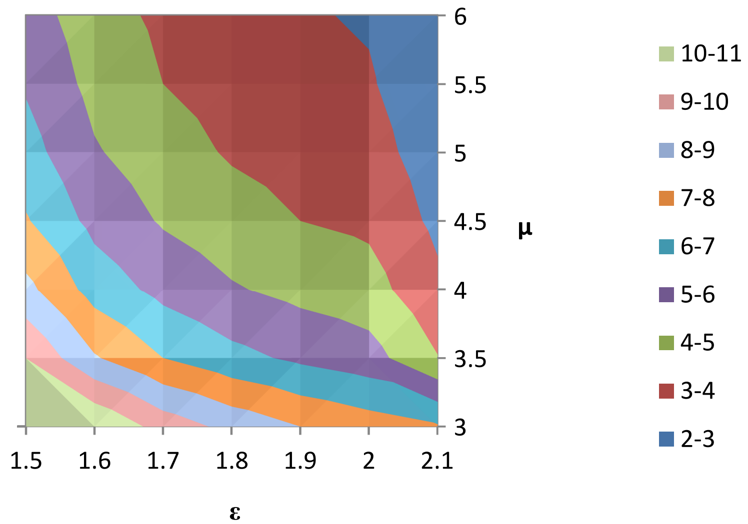
Success (Percentage of income variation explained)



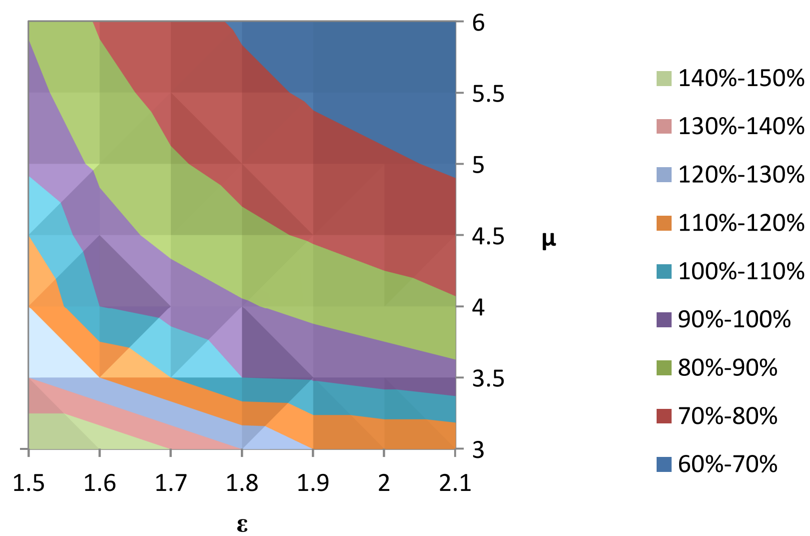
Notes: The upper panel presents the measure Λ, which is the ratio of the generalized human capital differences to traditional human capital differences. The lower panel presents the measure "success", which is the percentage of the income variation explained by capital input variation. In both panels,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



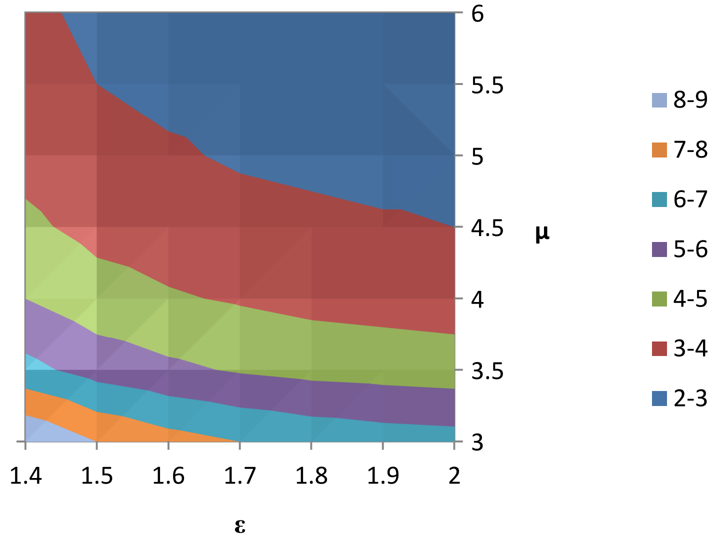
Success (Percentage of income variation explained)



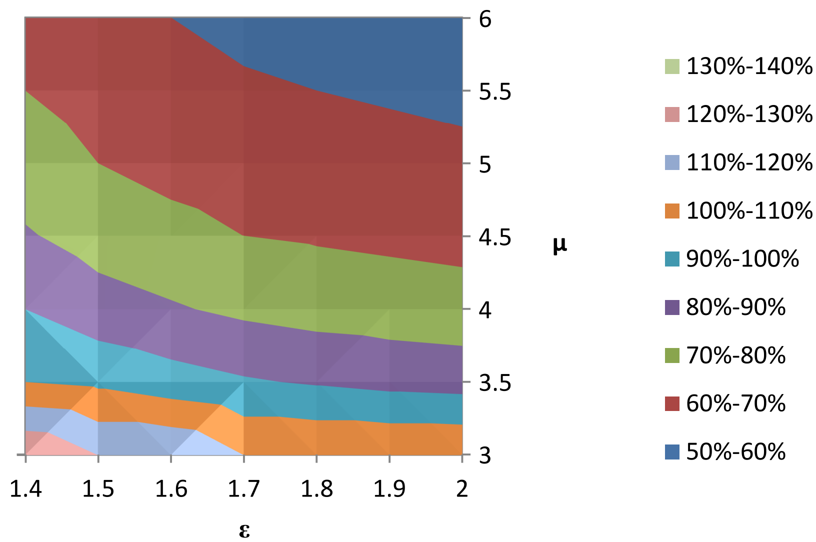
Notes: The upper panel presents the measure Λ, which is the ratio of the generalized human capital differences to traditional human capital differences. The lower panel presents the measure "success", which is the percentage of the income variation explained by capital input variation. In both panels,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



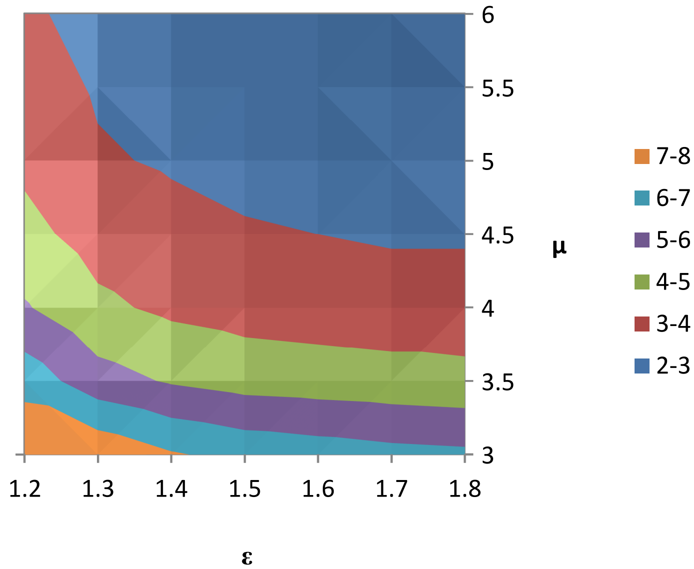
Success (Percentage of income variation explained)



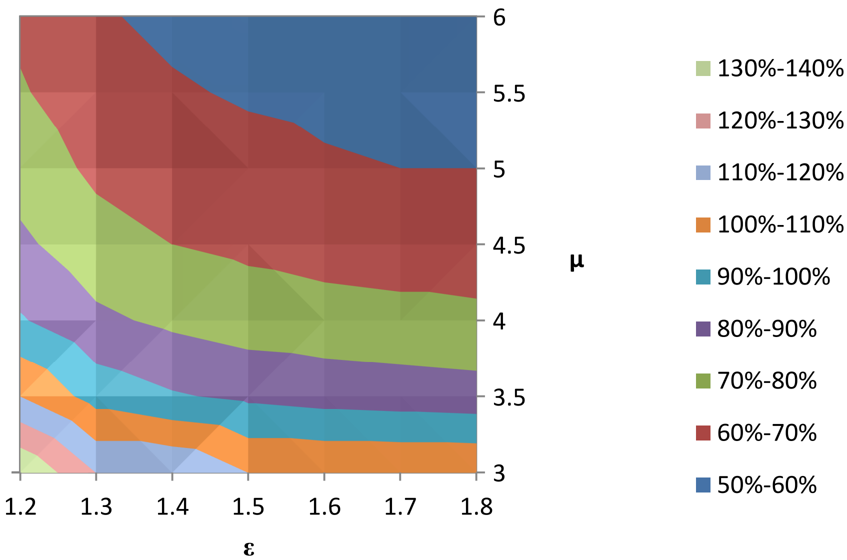
Notes: The upper panel presents the measure Λ, which is the ratio of the generalized human capital differences to traditional human capital differences. The lower panel presents the measure "success", which is the percentage of the income variation explained by capital input variation. In both panels,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

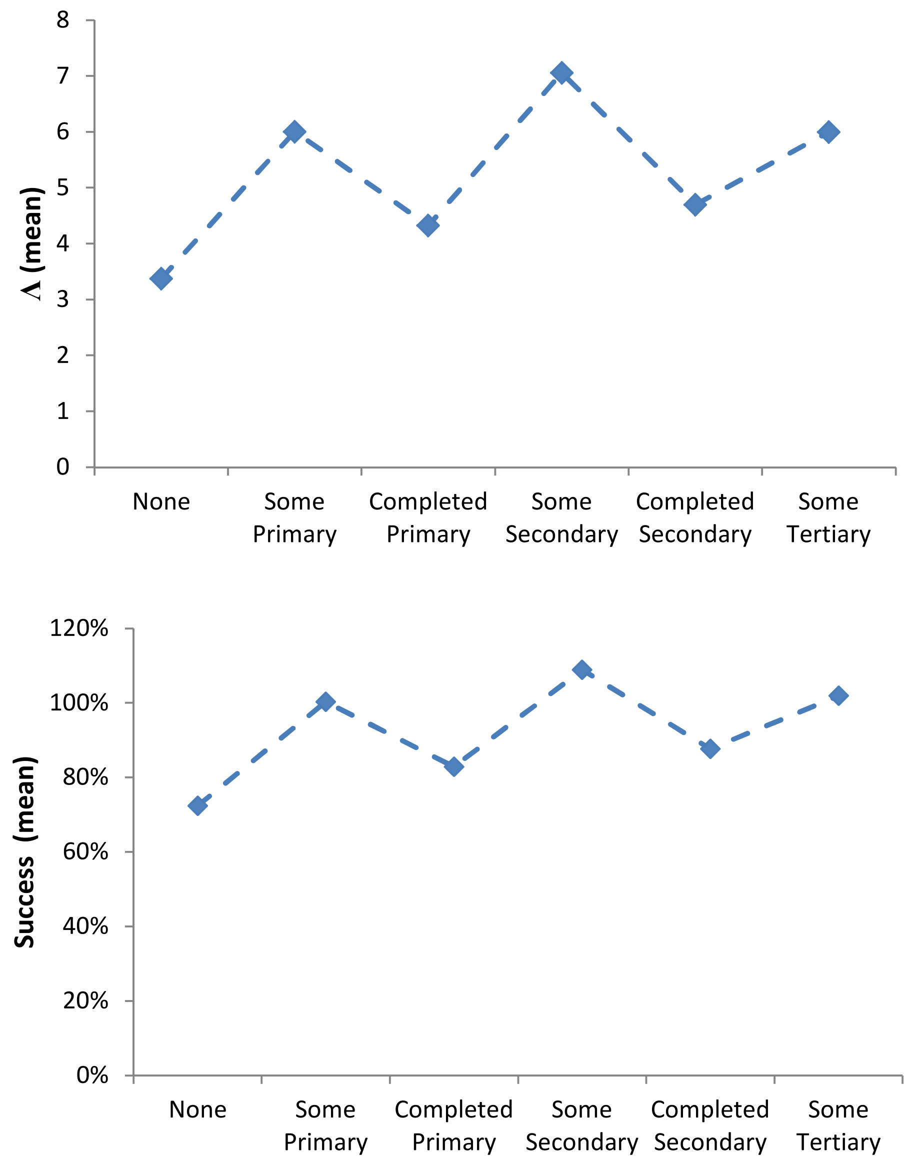


Success (Percentage of income variation explained)



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

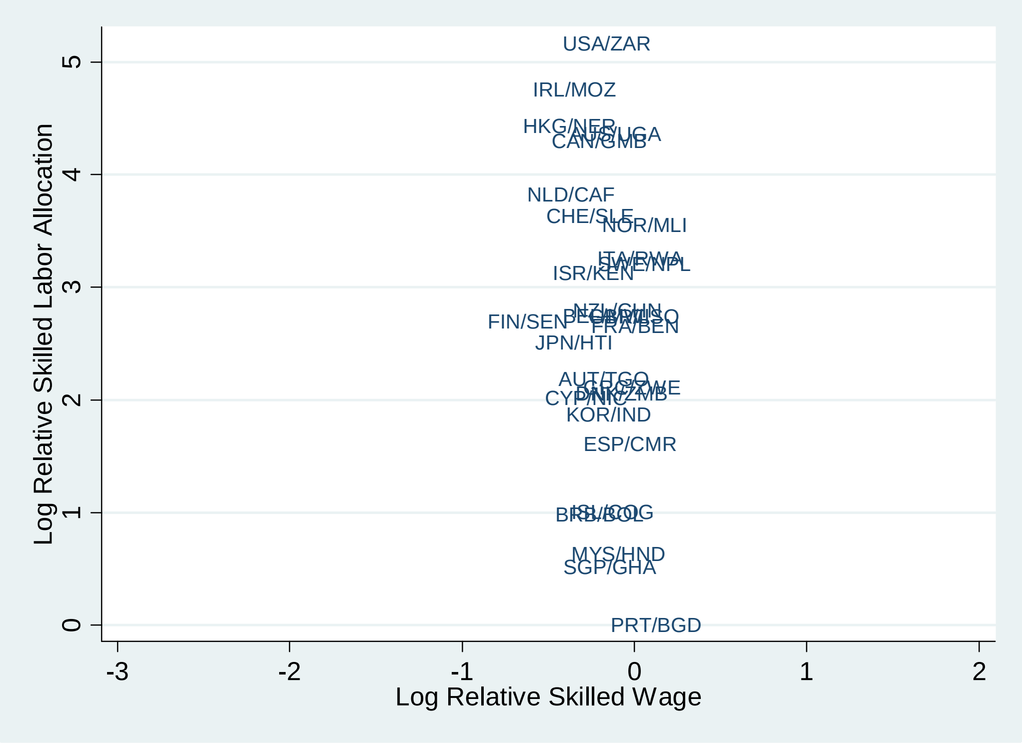


Figure A2.2: Calibrated Difference in Specialization across Countries

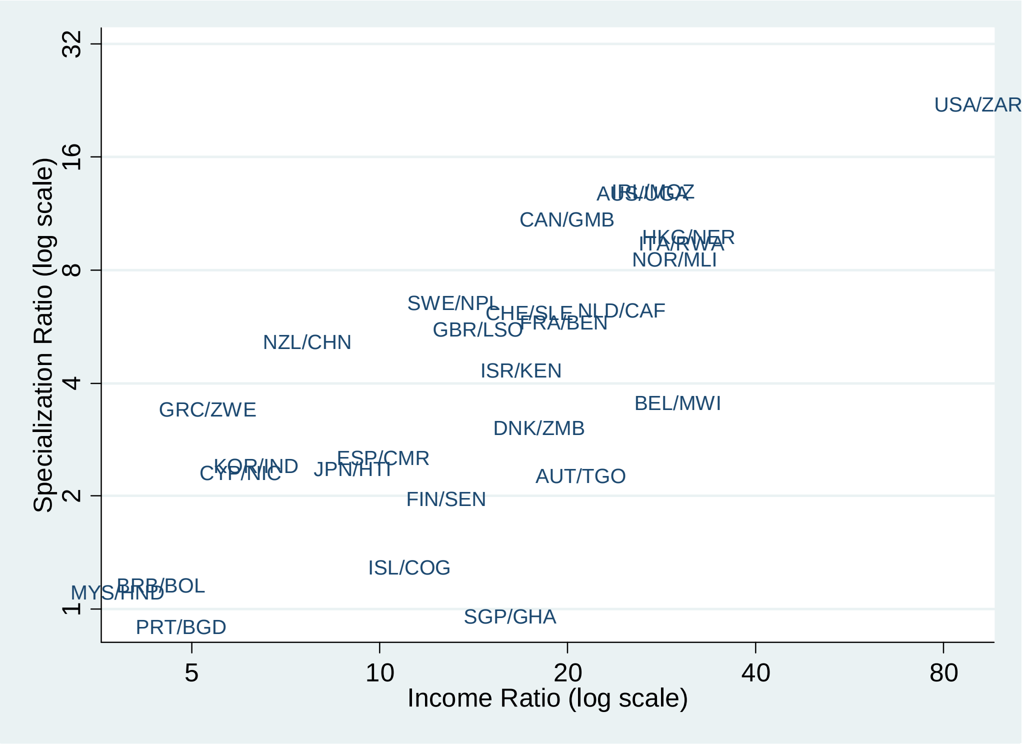


Table A1.1: Regression Estimates

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.