The Relative Efficiency of Skilled Labor across Countries: Measurement and Interpretation

Federico Rossi*

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ONLINE APPENDIX

A Data Appendix

IPUMS Data

This section describes the construction of the key variables from IPUMS USA and IPUMS International (Ruggles et al., 2019; Minnesota Population Center, 2019). All calculations and regressions on IPUMS data make use of the provided sample weights.

Wages. Weekly and hourly wages are constructed from the variable *incwage*, which reports the respondent's wage and salary income (except for some countries where this information is not available - see the "Country-Specific Notes" below). The information on hours, when available, is from the variable *hrswork1* (*uhrswork* in the US Census), which reports the number of hours worked in all jobs in either the previous week or a typical week (again, see the "Country-Specific Notes" for some exceptions).

Educational Attainment. Educational attainment is constructed from the variables *educd* in IPUMS USA and *edattaind* in IPUMS International, which record the highest level of completed schooling. Whenever these variables do not allow me to identify all 5 levels of educational attainment, I use additional information on the number of completed years of schooling (see the "Country-Specific Notes" for the details). I also construct an independent measure of years of schooling (for some of the robustness checks), based on the information in the *educd* and *edattaind* codes when possible, and otherwise imputed from the statutory duration of each education stage from the World Development Indicators (World Bank, 2017).

Country-Specific Notes.

*University of Warwick, Department of Economics, Coventry CV4 7AL, United Kingdom. Email: federico.rossi@warwick.ac.uk.

- **Brazil**. Separate variables on wage and self-employment incomes are not available. I use earned income as proxy for wage income for workers that declare to be wage employed, and as proxy for self-employment income for workers that declare to be self-employed. Year of immigration is only available for the 2010 cross-section. For the 1991 and 2000 cross-section, I identify a limited number of foreign-educated migrants using information on the place of residence 5 years before the Census.

- **India**. As discussed in the paper, hours worked are not available. To identify workers attached to the labor market (which are those included in the wage regressions), I use an indicator of full-time status. Self-employment income is not available.

- **Indonesia**. Self-employment income is not available.

- **Israel**. The educational variable does not allow to identify individuals with lower secondary education (or equivalent level). I impute this level of education based on available information on years of schooling. In particular, I assign lower secondary as educational attainment to (i) individuals that report "Primary or intermediate school" as educational attainment and at least 9 years of schooling, and (ii) individuals that report secondary school as educational attainment and less than "11 or 12" years of schooling (the two are grouped together). Year of immigration is available only in terms of time (generally 4-year) intervals; I use the mid-point of each interval, and discard observations in any open interval (i.e. "before 1948"). Hours worked are also available as categorical variable; I use the mid-point of each interval.

- **Jamaica**. The educational variable does not allow to identify individuals with lower secondary education (or equivalent level). I impute this level of education based on available information on years of schooling. As discussed in the IPUMS International documentation, the years of schooling variable appears to include pre-school, and its average is higher compared to other sources. Taking into account this, I assign lower secondary as educational attainment to individuals that report secondary school as educational attainment and 12 years of schooling or less (as opposed to 10, which would be the relevant threshold according to statutory durations). The choice of this threshold is based on the observation that the empirical distribution of reported years of schooling displays substantial peaks at 8 and 13, which correspond to the statutory durations of primary and upper secondary school plus 2. Self-employment income is not available.

- **Mexico**. Separate variables on wage and self-employment incomes are not available. I use earned income as proxy for wage income for workers that declare to be wage employed, and as proxy for self-employment income for workers that declare to be self-employed.

- **Panama**. As discussed in the paper, hours worked are not available. Wage regressions are estimated on a sample including all employed workers (with available information on wage income). Self-employment income is not available.

- **Trinidad and Tobago**. Hours worked are also available as categorical variable; I use the mid-point of each interval.

- **United States**. The IPUMS USA data include additional information on the number of weeks worked in the previous year, which I combine with the number of hours usually worked per week to compute annual hours (and with annual wage income to compute hourly wages). The sample of workers attached to the labor market used for the wage regressions includes employed workers with at least 30 hours worked per week and 30 weeks worked in the previous year. In the 1990 sample, years since migration is available only in terms of time intervals; I use the mid-point of each interval, and discard observations in any open interval (i.e. "before 1949").

- **Uruguay**. Hours worked only refer to the main occupation. Self-employment income is not available.

- **Venezuela**. Separate variables on wage and self-employment incomes are not available. I use earned income as proxy for wage income for workers that declare to be wage employed, and as proxy for self-employment income for workers that declare to be self-employed.

PIAAC Data

I use data from Rounds 1-3 of the Survey of Adult Skills, part of the PIAAC 1^{st} Cycle (OECD, 2016a). The Public Use Files include data for 35 countries; I exclude Russia as the sample is not nationally representative (OECD, 2016b), leaving 34 countries. The United States participated to both Rounds 1 and 3; the data used refer to Round 1. The data construction follows closely Hanushek et al. (2015). I use the first plausible value for the numeracy domain, and standardize it to have an average of 0 and a standard deviation of 1 when pooling all countries, with observations re-weighted so that each country has an equal weight. The education variable is constructed from information on the highest obtained qualification, with high-school graduates corresponding to ISCED leves 3A, 3B and 3C (2+ years), and college graduates to ISCED 5A and 6; when this information is not available (Canada and Estonia), I impute the education level using years of education. For wages, I use the provided PPP corrected hourly earnings excluding bonuses. For 9 countries, only wage deciles are available; in these cases I impute the median wage of each decile provided in Hanushek et al. (2015) whenever available. The sample is restricted to individuals working 30 hours per week or more; when hours are not available, I focus on individuals declaring to be employed full-time (Austria) or simply to be employed with positive earnings (Canada). All calculations use the provided sample weights.

B Measuring Relative Skill Efficiency: Additional Material

This Appendix includes additional material on the measurement of relative skill efficiency. The first three sections describe in greater detail the implementation of some of the robustness exercises in the paper. The fourth section illustrates the implications of different production technologies, discussed verbally in the paper. The fifth section covers additional extensions and robustness checks (not in the paper). The last section includes country-level results.

B.1 Experience and Gender

I mantain the assumption that workers within skill groups are perfect substitutes, but I allow their efficiency to depend on potential experience exp and gender g (in addition to their educational attainment). I categorize potential experience into seven groups based on 5-year intervals, and I use tertiary (upper secondary) educated, unexperienced, males as baseline high-skill (low-skill) workers. The labor stocks are given by

$$\tilde{H}_c = \sum_{n \in \mathcal{H}} \sum_{exp \in \mathcal{E}} \sum_{g \in \mathcal{G}} \frac{w_{H,c,n,exp,g}}{w_{H,c,\text{tertiary,0to4,male}}} \tilde{H}_{c,n,exp,g} \tag{1}$$

$$\tilde{L}_c = \sum_{m \in \mathcal{L}} \sum_{exp \in \mathcal{E}} \sum_{g \in \mathcal{G}} \frac{w_{L,c,m,exp,g}}{w_{L,c,\text{upper secondary,0to4,male}}} \tilde{L}_{c,m,exp,g} \tag{2}$$

where $w_{H,c,n,exp,g}$, $w_{L,c,m,exp,g}$, $\tilde{H}_{c,n,exp,g}$ and $\tilde{L}_{c,m,exp,g}$ denote the wages and total hours worked by high- and low-skill workers with experience exp, gender g and education levels n and m, with $exp \in \mathcal{E} = \{\text{0 to 4, 5 to 9, 10 to 14, 15 to 19, 20 to 24, 25 to 29, 30 or more}\}$ and $g \in \mathcal{G} = \{\text{male, female}\}$. Given that sample sizes are sometimes small at the education × experience × gender level, I assume that within skill levels the effects of these characteristics on log wages are not interactive, so that one can write

$$\frac{w_{H,c,n,exp,g}}{w_{H,c,\text{tertiary},\text{0to4},\text{male}}} = e^{\beta_{H,n}} e^{\lambda_{H,exp}} e^{\mu_{H,g}} \tag{3}$$

$$\frac{w_{L,c,m,exp,g}}{w_{L,c,\text{upper secondary},\text{0to4},\text{male}}} = e^{\beta_{L,m}} e^{\lambda_{L,exp}} e^{\mu_{L,g}} \tag{4}$$

with the normalizations $\beta_{H,\text{tertiary}} = \lambda_{H,\text{0to4}} = \mu_{H,\text{male}} = 0$ and $\beta_{L,\text{upper secondary}} = \lambda_{L,\text{0to4}} = \mu_{L,\text{male}} = 0$. I estimate all parameters from log-wage regressions with educational, experience and gender dummies (interacted with skill level) as controls, and I calculate the skill premium as the wage ratio between baseline high- and low-skill workers. With the estimates of the relative supply and the skill premium at hand, I calculate relative skill efficiency from equation (8) in the paper.

B.2 Sectors

B.2.1 Sector-Level Elasticity of Substitution

The calibration of the sector-level elasticity $\tilde{\sigma}$ relies on the theoretical results in Oberfield and Raval (2014). These imply that the aggregate elasticity of substitution σ can be written as a convex combination of the sector-level elasticity, $\tilde{\sigma}$, and a term capturing the magnitude of the reallocation effect

$$\sigma = (1-\chi)\tilde{\sigma} + \chi\left[\bar{\alpha}\bar{\zeta} + (1-\bar{\alpha})\epsilon\right] \tag{5}$$

where $\chi \in [0,1]$ is a measure of cross-sector heterogeneity in skill intensity, $\bar{\alpha}$ and $\bar{\zeta}$ are weighted averages of the sectoral capital shares and elasticities of substitution between capital and labor, and ϵ is the demand elasticity of substitution between sectors. The terms in (5) are defined as follows. Denote by a the average high-skill share of wage payments,

$$a = \sum_s \theta_s a_s$$

where a_s is the high-skill share of wage payments in sector s,

$$a_s = \frac{w_{H,s}\tilde{H}_s}{w_{H,s}\tilde{H}_s + w_{L,s}\tilde{L}_s}$$

and θ_s is the sectoral share of wage payments,

$$\theta_s = \frac{w_{H,s}\tilde{H}_s + w_{L,s}\tilde{L}_s}{\sum_s w_{H,s}\tilde{H}_s + w_{L,s}\tilde{L}_s}$$

The heterogeneity index χ is defined as

$$\chi = \sum_s \frac{(a_s - a)^2}{a(1-a)}\theta_s$$

Let the capital share of and the elasticity of substitution between capital and the labor bundle in sector s be, respectively, α_s and ζ_s. The weighted averages $\bar{\alpha}$ and $\bar{\zeta}$ are defined as

$$\bar{\alpha} = \sum_s \frac{(a_s - a)^2 \theta_s}{\sum_j (a_j - a)^2 \theta_j} \alpha_s$$

$$\bar{\zeta} = \sum_s \frac{(a_s - a)^2 \theta_s \alpha_s}{\sum_j (a_j - a)^2 \theta_j \alpha_j} \zeta_s$$

Conditional on US-specific values for χ, $\bar{\alpha}$, $\bar{\zeta}$ and ϵ, I can back out the value of $\tilde{\sigma}$ that is consistent with $\sigma = 1.5$, as estimated in the literature based on US data. The computation of the heterogeneity index yields $\chi = 0.075$, which implies that the sector-level elasticity is in fact close to the aggregate one, and largely insensitive to the values of $\bar{\alpha}$, $\bar{\zeta}$ and ϵ. I set $\bar{\alpha} = 1/3$ and $\bar{\zeta} = 1$, i.e. sectoral Cobb-Douglas production functions with capital shares of 1/3, and $\epsilon = 0$, as estimated in Herrendorf et al. (2013); the resulting sector-level elasticity is $\tilde{\sigma} = 1.59$.[1]

B.2.2 Counterfactual Exercise

This subsection describes the counterfactual exercise on sectoral composition mentioned in the paper. I ask the following question: how large would the cross-country variation in the inferred aggregate relative skill efficiency be, if all countries had the same sectoral shares of employment (by education) as the United States? In other words, to what extent would equalizing the sectoral composition (keeping fixed the sector-level relative efficiencies and the total number of high- and low-skill workers) close the cross-country gaps documented in the paper?

Answering this question requires more structure on the productive and the demand sides of the economy. I impose the following simplifying assumptions

(A1) The sectoral production function is

$$Y_{c,s} = Z_{c,s} K_{c,s}^{\alpha} \left[(A_{H,c,s} H_{c,s})^{\frac{\tilde{\sigma}-1}{\tilde{\sigma}}} + (A_{L,c,s} L_{c,s})^{\frac{\tilde{\sigma}-1}{\tilde{\sigma}}} \right]^{\frac{(1-\alpha)\tilde{\sigma}}{\tilde{\sigma}-1}}$$

where $K_{c,s}$ is physical capital in sector s and $Z_{c,s}$ is a technological term capturing total factor productivity.

(A2) The prices of the sectoral goods are exogenous to the allocation of labor (as for small open economies).

(A3) Labor and physical capital are not mobile across sectors.

(A4) Conditional on educational attainment, human capital does not vary across sectors.

Let $w_{H,c,s,n}$ and $w_{L,c,s,m}$ be the wages paid to skilled and unskilled workers employed in sector s and belonging to educational groups n and m, where $n \in \{\text{some tertiary, tertiary}\}$ and $m \in \{\text{primary, lower secondary, upper secondary}\}$. Moreover, let $\widetilde{H}^{\text{bodies}}_{c,s,n}$ and $\widetilde{H}^{\text{hours}}_{c,s,n}$ ($\widetilde{L}^{\text{bodies}}_{c,s,m}$ and $\widetilde{L}^{\text{hours}}_{c,s,M}$) be the numbers of high-skill (low-skill) workers and total hours worked in sector s for educational group

[1]Given the low value of χ, reasonable deviations from these assumptions have minimal impact on the calibrated $\tilde{\sigma}$. For example, using the sector-specific capital shares and elasticities of substitution between capital and labor estimated in Herrendorf et al. (2015) leads to $\tilde{\sigma} = 1.60$ (for this calculation I impute the "services" values for both low- and high-skill services); using $\epsilon = 0.5$ as in Buera and Kaboski (2009) leads to $\tilde{\sigma} = 1.57$.

n (m), with $\widetilde{H}^{\text{bodies}}_{c,n}$ and $\widetilde{H}^{\text{hours}}_{c,n}$ ($\widetilde{L}^{\text{bodies}}_{c,m}$ and $\widetilde{L}^{\text{hours}}_{c,M}$) being the corresponding totals across sectors. One can then write $w_{H,c,n}$ and $w_{L,c,m}$ as the geometric averages of these wages across sectors

$$\begin{aligned} w_{H,c,n} &= \prod_s \left(w_{H,c,s,n}\right)^{\frac{\widetilde{H}^{\text{bodies}}_{c,s,n}}{\widetilde{H}^{\text{bodies}}_{c,n}}} \\ w_{L,c,m} &= \prod_s \left(w_{L,c,s,m}\right)^{\frac{\widetilde{L}^{\text{bodies}}_{c,s,m}}{\widetilde{L}^{\text{bodies}}_{c,m}}} \end{aligned} \tag{6}$$

where the weights $\frac{\widetilde{H}^{\text{bodies}}_{c,s,n}}{\widetilde{H}^{\text{bodies}}_{c,n}}$ and $\frac{\widetilde{L}^{\text{bodies}}_{c,s,m}}{\widetilde{L}^{\text{bodies}}_{c,m}}$ are the education-specific shares of workers employed in sector s (since the unit of observation for the computation of $w_{H,c,n}$ and $w_{L,c,m}$ is the worker, not weighted by hours worked).[2]

For every educational group n and m, I construct counterfactual allocations of employment and hours across sectors based on the (education-specific) sectoral employment and hours shares in the US,

$$\widetilde{H}^{C,\text{bodies}}_{c,s,n} = \left(\frac{\widetilde{H}^{\text{bodies}}_{n,US,s}}{\widetilde{H}^{\text{bodies}}_{n,US}}\right)\widetilde{H}^{\text{bodies}}_{n,c} \qquad \widetilde{L}^{C,\text{bodies}}_{c,s,m} = \left(\frac{\widetilde{L}^{\text{bodies}}_{m,US,s}}{\widetilde{L}^{\text{bodies}}_{m,US}}\right)\widetilde{L}^{\text{bodies}}_{m,c}$$

$$\widetilde{H}^{C,\text{hours}}_{c,s,n} = \left(\frac{\widetilde{H}^{\text{hours}}_{n,US,s}}{\widetilde{H}^{\text{hours}}_{n,US}}\right)\widetilde{H}^{\text{hours}}_{n,c} \qquad \widetilde{L}^{C,\text{hours}}_{c,s,m} = \left(\frac{\widetilde{L}^{\text{hours}}_{m,US,s}}{\widetilde{L}^{\text{hours}}_{m,US}}\right)\widetilde{L}^{\text{hours}}_{m,c}$$

Denote the equilibrium wages prevailing at this counterfactual allocation as $w^C_{H,c,s,n}$ and $w^C_{L,c,s,m}$. Under assumptions (A1)-(A4), these counterfactual wages can be written as[3]

$$\begin{aligned} w^C_{H,c,s,n} &= w_{H,c,s,n}\left(\frac{\widetilde{H}^{C,\text{hours}}_{c,s,n}}{\widetilde{H}^{\text{hours}}_{c,s,n}}\right)^{-\alpha}\left[\frac{1+\left(\frac{A_{L,c,s,m}Q_{L,c,m}\widetilde{L}^{C,\text{hours}}_{c,s,m}}{A_{H,c,s,n}Q_{H,c,n}\widetilde{H}^{C,\text{hours}}_{c,s,n}}\right)^{\frac{\tilde{\sigma}-1}{\tilde{\sigma}}}}{1+\left(\frac{A_{L,c,s,m}Q_{L,c,m}\widetilde{L}^{\text{hours}}_{c,s,m}}{A_{H,c,s,n}Q_{H,c,n}\widetilde{H}^{\text{hours}}_{c,s,n}}\right)^{\frac{\tilde{\sigma}-1}{\tilde{\sigma}}}}\right]^{\frac{1-\alpha\tilde{\sigma}}{\tilde{\sigma}-1}} \\ w^C_{L,c,s,m} &= w_{L,c,s,m}\left(\frac{\widetilde{L}^{C,\text{hours}}_{c,s,m}}{\widetilde{L}^{\text{hours}}_{c,s,m}}\right)^{-\alpha}\left[\frac{1+\left(\frac{A_{H,c,s,n}Q_{H,c,n}\widetilde{H}^{C,\text{hours}}_{c,s,n}}{A_{L,c,s,m}Q_{L,c,m}\widetilde{L}^{C,\text{hours}}_{c,s,m}}\right)^{\frac{\tilde{\sigma}-1}{\tilde{\sigma}}}}{1+\left(\frac{A_{H,c,s,n}Q_{H,c,n}\widetilde{H}^{\text{hours}}_{c,s,n}}{A_{L,c,s,m}Q_{L,c,m}\widetilde{L}^{\text{hours}}_{c,s,m}}\right)^{\frac{\tilde{\sigma}-1}{\tilde{\sigma}}}}\right]^{\frac{1-\alpha\tilde{\sigma}}{\tilde{\sigma}-1}} \end{aligned} \tag{7}$$

I set $\alpha = 1/3$, and compute counterfactual wages for all educational groups using (7). With these at

[2]As discussed in the paper, $w_{H,c,n}$ and $w_{L,c,m}$ are computed on a restricted sample of workers (wage workers with relatively high labor market attachment). As the sectoral shares of employment in this subsample are not exactly equal to $\frac{\widetilde{H}^{\text{bodies}}_{c,s,n}}{\widetilde{H}^{\text{bodies}}_{c,n}}$ and $\frac{\widetilde{L}^{\text{bodies}}_{c,s,m}}{\widetilde{L}^{\text{bodies}}_{c,m}}$, which are calculated over the whole population of employed workers, the expressions in (6) hold up to a small approximation error.

[3]Assumption (A4) allows me to abstract from any change in the sector-level average human capital following the reallocation of labor across sectors.

hand, I compute the counterfactual skill premium and relative skill supply as

$$\begin{aligned}
\frac{w^C_{H,c}}{w^C_{L,c}} &= \frac{\prod_s \left(w^C_{H,c,s,\text{tertiary}}\right)^{\frac{\widetilde{H}^{C,\text{bodies}}_{c,s,\text{tertiary}}}{\widetilde{H}^{\text{bodies}}_{c,\text{tertiary}}}}}{\prod_s \left(w^C_{L,c,s,\text{upper sec}}\right)^{\frac{\widetilde{L}^{C,\text{bodies}}_{c,s,\text{upper sec}}}{\widetilde{L}^{\text{bodies}}_{c,\text{upper sec}}}}} \\
\frac{\tilde{H}^C_c}{\tilde{L}^C_c} &= \frac{\frac{w^C_{H,1,c}}{w^C_{H,c,\text{tertiary}}}\widetilde{H}^{\text{hours}}_{1,c} + \ldots + \frac{w^C_{H,N,c}}{w^C_{H,c,\text{tertiary}}}\widetilde{H}^{\text{hours}}_{N,c}}{\frac{w^C_{L,1,c}}{w^C_{L,c,\text{upper sec}}}\widetilde{L}^{\text{hours}}_{1,c} + \ldots + \frac{w^C_{L,M,c}}{w^C_{L,c,\text{upper sec}}}\widetilde{L}^{\text{hours}}_{M,c}}
\end{aligned} \tag{8}$$

Let RSE_c be the "aggregate" relative skill efficiency, i.e. the relative skill efficiency estimated when postulating an aggregate production function

$$RSE_c = \left(\frac{w_{H,c}}{w_{L,c}}\right)^{\frac{\sigma}{\sigma-1}} \left(\frac{\tilde{H}_c}{\tilde{L}_c}\right)^{\frac{1}{\sigma-1}}$$

where σ is the aggregate elasticity of substitution. The counterfactual skill premium and relative supply in (8) can be used to compute a counterfactual version of RSE_c,

$$RSE^C_c = \left(\frac{w^C_{H,c}}{w^C_{L,c}}\right)^{\frac{\sigma}{\sigma-1}} \left(\frac{\tilde{H}^C_c}{\tilde{L}^C_c}\right)^{\frac{1}{\sigma-1}}$$

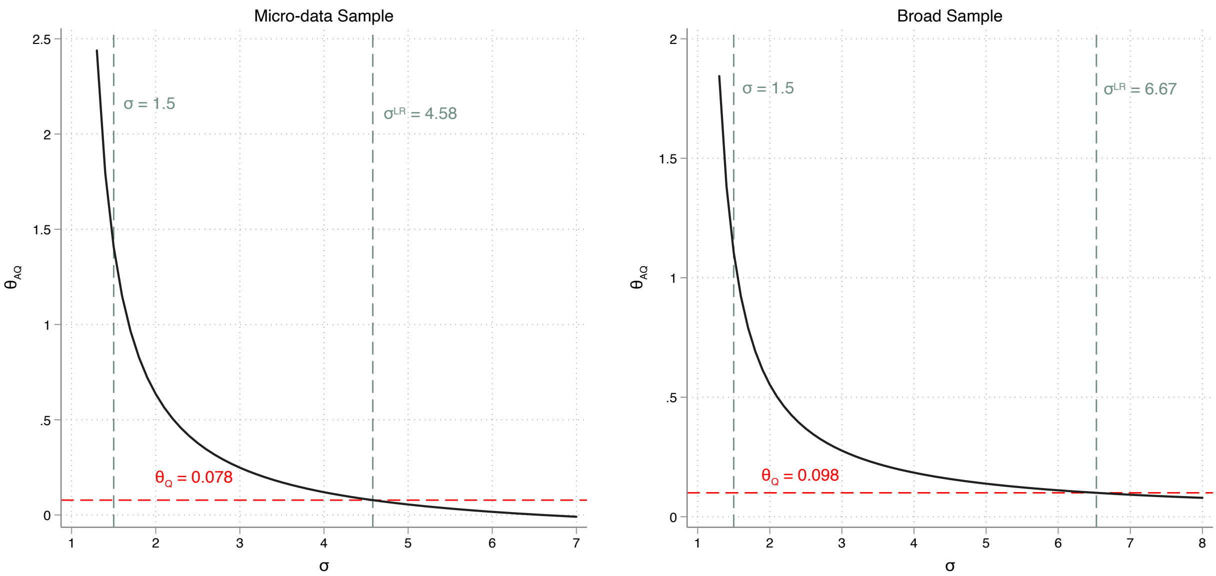
which would emerge in a world where sectorial employment shares were equalized. This counterfactual is reported in column 8 of Table B.3. Compared to the baseline RSE_c (reported in column 1), the counterfactual is slightly less variable across countries (the elasticity with respect to GDP is 12% lower). Intuitively, the counterfactual reallocation results, for poorer countries, in higher employment shares in sectors with higher relative skill efficiency, which contribute to a higher overall skill premium and a marginally lower cross-country variation in relative skill efficiency. This effect is small because a large part of the cross-country variation takes place within sectors, as showed in Table II of the paper.

B.3 Elasticity of Substitution

The left panel of Figure B.1 shows the micro-data sample value of θ_{AQ} from equation (9) of the paper as a function of σ, given the θ_W and $\theta_{\tilde{H}/\tilde{L}}$ reported in Table I. The first vertical line highlights $\sigma = 1.5$, that gives the baseline estimate of $\theta_{AQ} = 1.408$ in Table I. The second vertical line highlights the implied long-run elasticity of substitution σ^{LR}, defined in Section II.C as the value of σ that implies no cross-country differences in the skill bias of technology, that is $\theta_A = 0$ and $\theta_{AQ} = \theta_Q$. Given equation (9), this can be computed as $\sigma^{LR} = (\theta_Q + \theta_{\tilde{H}/\tilde{L}})/(\theta_Q - \theta_W)$. Using the estimate for the micro-data sample in row (2) of Table III, $\theta_Q = 0.078$, I find $\sigma^{LR} = 4.58$. The value of σ for which θ_{AQ} becomes 0 is instead given by $\theta_{\tilde{H}/\tilde{L}}/\theta_W = 6.60$.

The right panel shows the corresponding quantities for the broad sample. The long-run elasticity of substitution is somewhat larger but still in the ballpark of the estimates in Hendricks and Schoellman (2020) and Bils et al. (2020). Given that $\theta_W = 0$ for the broad sample, θ_{AQ} approaches 0 only in the limit as σ goes to infinity.

Figure B.1: Relative Skill Efficiency and the Elasticity of Substitution



Notes: The figure plots the value of the elasticity of relative skill efficiency θ_{AQ} (solid line) from equation (9) of the paper as a function of the elasticity of substitution σ, for the micro-data and broad samples. The two dashed vertical lines highlight respectively the baseline value of $\sigma = 1.5$ and the implied long-run elasticity of substitution σ^{LR}, defined in Section II.C. The horizontal dashed line highlights the baseline estimate of θ_Q for each sample (from row (2) of Table III).

B.4 Different Production Technologies

B.4.1 Capital-Skill Complementarity

This section studies the consequences of allowing for capital-skill complementarity in the production technology. Following Krusell et al. (2000), I distinguish between two types of capital: equipment K_c^E and structures K_c^S. The production function is assumed to be

$$Y_c = F_c\left(K_c^S, \left[\left(A_{L,c}Q_{L,c}\tilde{L}_c\right)^{\frac{\sigma-1}{\sigma}} + \left[\left(A_{H,c}Q_{H,c}\tilde{H}_c\right)^{\frac{\eta-1}{\eta}} + \left(A_{K,c}K_c^E\right)^{\frac{\eta-1}{\eta}}\right]^{\frac{\sigma-1}{\sigma}\frac{\eta}{\eta-1}}\right]^{\frac{\sigma}{\sigma-1}}\right)$$

where σ is the elasticity of substitution between low-skill labor and high-skill labor (or equipment) and η is the elasticity of substitution between high-skill labor and equipment. This production function displays capital-skill complementarity if $\sigma > \eta$, i.e. if equipment is more substitutable with low-skill labor. The skill premium can be written as

$$\frac{w_{H,c}}{w_{L,c}} = \left[\underbrace{\left(1 + \left(\frac{A_{K,c}K_c^E}{A_{H,c}Q_{H,c}\tilde{H}_c}\right)^{\frac{\eta-1}{\eta}}\right)^{\frac{\sigma-\eta}{(\sigma-1)(\eta-1)}} \left(\frac{A_{H,c}Q_{H,c}}{A_{L,c}Q_{L,c}}\right)}_{\text{Relative Skill Efficiency}}\right]^{\frac{\sigma-1}{\sigma}} \left(\frac{\tilde{H}_c}{\tilde{L}_c}\right)^{-\frac{1}{\sigma}} \tag{9}$$

Equation (9) illustrates how capital-skill complementarity affects the interpretation of relative skill efficiency. If $\sigma > \eta$ - the empirically relevant case according to Krusell et al. (2000)'s estimates - the skill premium is increasing in the ratio between effective equipment and high-skill labor, everything else equal. If rich countries are relatively abundant in equipment, capital-skill complementarity reduces the variation in $\frac{A_{H,c}Q_{H,c}}{A_{L,c}Q_{L,c}}$ needed to rationalise a relatively flat skill premium across countries. In a sense, this mechanism can be seen as a particular rationalization of skill-biased technological differences across countries: rich countries are relatively more abundant in the type of capital that is more complementary to high-skill labor.

A question of interest is whether this mechanism can account for a large part of the variation in relative skill efficiency. The first order conditions for equipment and high-skill labor can be written as (denoting the rental rate of equipment as r_c)

$$\frac{r_c K_c^E}{w_{H,c}\tilde{H}_c} = \left(\frac{A_{K,c}K_c^E}{A_{H,c}Q_{H,c}\tilde{H}_c}\right)^{\frac{\eta-1}{\eta}}$$

which implies that the capital-skill complementarity term in (9) can be quantified with (i) data on the relative income share of equipment and high-skill labor, and (ii) a calibrated value for η. For the share of equipment, I use data from the Capital Detail File of the Penn World Table, Version 9.1 (Feenstra et al., 2015); I compute the sum of the shares of capital compensation of "machinery and (non-transport) equipment" and "transport equipment", and multiply it by an assumed overall capital share of 1/3 (common across countries). I calculate the income share of high-skill labor from the IPUMS data, as $\frac{2}{3} \times \frac{w_{H,c}\tilde{H}_c}{w_{H,c}\tilde{H}_c + w_{L,c}\tilde{L}_c}$. Finally, I use the estimate of $\eta = 0.67$ from Krusell et al. (2000).

The last column of Table B.3 shows the results. The elasticity of $\frac{A_{H,c}Q_{H,c}}{A_{L,c}Q_{L,c}}$ with respect to GDP per worker is about half of the baseline one. The capital-skill complementarity term in equation (9) is larger for rich countries, which are relatively more abundant in equipment; this term is absorbed by the baseline estimates in column 1, while it is netted out in column 11. Overall, the relative abundance of equipment can account for a non trivial part for the cross-country variation in relative skill efficiency (consistently with the conclusion of the paper that this variation is to a large extent not driven by relative human capital).

B.4.2 Division of Labor

This section introduces a conceptual framework similar to Jones (2014b) to highlight the potential role of the division of labor. High-skill production involves the implementation of differentiated tasks. In a given country c, this is achieved through the sorting of high-skill workers into N_c occupations, which correspond to different bundles of tasks. N_c might vary across countries both because some advanced tasks might not be performed at all in some countries (e.g., the development of mRNA vaccines only happening in rich countries), and because different tasks might be performed by separate specialized workers in some countries and by generalist workers in others (e.g., daylight and façade designers being different occupations in some countries, with the corresponding tasks being performed by generalist architects in others).

Following Jones (2014b), higher labor specialization has both direct benefits and costs on labor productivity, described respectively by increasing and possibily country-specific functions $f_c(N_c)$ and $d_c(N_c)$. The benefits $f_c(N_c)$ capture the idea that by focusing on a narrower set of tasks workers can become better at what they do, or possibly that a more diverse set of available activities allows for a better allocation of heterogeneous talent as in Jaimovich (2011). The costs $d_c(N_c)$ capture coordination costs associated with involving a larger number of workers in the production process of a given good. The high-skill aggregator is then given by

$$H_c = \left[\sum_{j=1}^{N_c}\left(Q_{H,c}\frac{f_c(N_c)}{d_c(N_c)}\tilde{H}_{j,c}\right)^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}$$

where $\tilde{H}_{j,c}$ is the number of workers in occupation j (or their total hours), and η is the elasticity of substitution between the inputs of different occupations. If $\eta < \infty$, wage equalization across occupations implies $\tilde{H}_{j,c} = \tilde{H}_c/N_c$. The skill premium can be written as

$$\frac{w_{H,c}}{w_{L,c}} = \left[\underbrace{\frac{A_{H,c}Q_{H,c}}{A_{L,c}Q_{L,c}} N_c^{\frac{1}{\eta-1}} \frac{f_c(N_c)}{d_c(N_c)}}_{\text{Relative Skill Efficiency}} \right]^{\frac{\sigma-1}{\sigma}} \left(\frac{\tilde{H}_c}{\tilde{L}_c} \right)^{-\frac{1}{\sigma}} \tag{10}$$

This expression shows that the relative skill efficiency computed in the paper possibly incorporates different effects of the organization of production. First, if $\eta \in (1, \infty)$ a higher N_c increases the relative productivity of high-skill labor thorugh a “love for variety” type of effect. Second, relative skill efficiency is higher in countries that strike a better balance between benefits and costs of high-skill labor specialization.

As emphasized in Jones (2014b), any cross-country variation in these organizational factors might be driven by a variety of mechanisms. The complementarity between workers specializing on different tasks can lead to multiple equilibria, with otherwise identical countries ending up with different values of N_c. Differences in various institutional factors affecting the steepness of the $f_c(N_c)$ and $d_c(N_c)$ functions imply that the output-maximizing N_c might be different across countries. Moreover, N_c might be partially endogenous to the supply of skilled labor, in the spirit of models of directed technical change (Acemoglu, 2002; Caselli and Coleman, 2006). Quantifying the countribution of differences in the organization of production to gaps in relative skill efficiency, as well as the relative role of the fundamental drivers of these differences, is an interesting task for future research.

B.5 Additional Exercises

B.5.1 Mincerian-Based Skill Premia

As shown in Table I of the paper, constructing skill premia and relative supplies using a Mincerian return of 10% common across countries leads to an overstatement of the cross-country variation in relative skill efficiency. This is because the skill premium is in fact somewhat higher in poor countries, as opposed to constant across countries as implied by a common Mincerian return. This section documents that this finding also applies to the collections of Mincerian returns used in the literature, and proposes a possible explanation based on the non-linearity of returns with respect to years of schooling.

Table B.1 shows the skill premium, relative supply and relative skill efficiency based on alternative country-specific estimates of the Mincerian return (relative supplies are constructed here using educational attainment data for the working age population). The first three columns use the estimates collected in Caselli et al. (2016) (I use the values for the 2000s). Columns 4-6 use the Mincerian returns estimated in Montenegro and Patrinos (2014), a collection that, while not yet widely used in the development accounting literature, offers more comparable estimates from harmonized household surveys. Columns 7-9 use Mincerian returns estimated from the IPUMS and IPUMS International data used for the core analysis of the paper.

For all sources, the resulting skill premium is flatter across countries compared to the baseline in Table I of the paper. Even when using the same (IPUMS) data, the elasticities of the Mincerian-based skill premium with respect to GDP per worker is 1/4 of the corresponding baseline elasticity; the estimates of the relative supply are instead similar. As a result of a less variable skill premium and an equally variable relative supply, Mincerian-based estimates of relative skill efficiency display more variability across countries compared to the baseline.

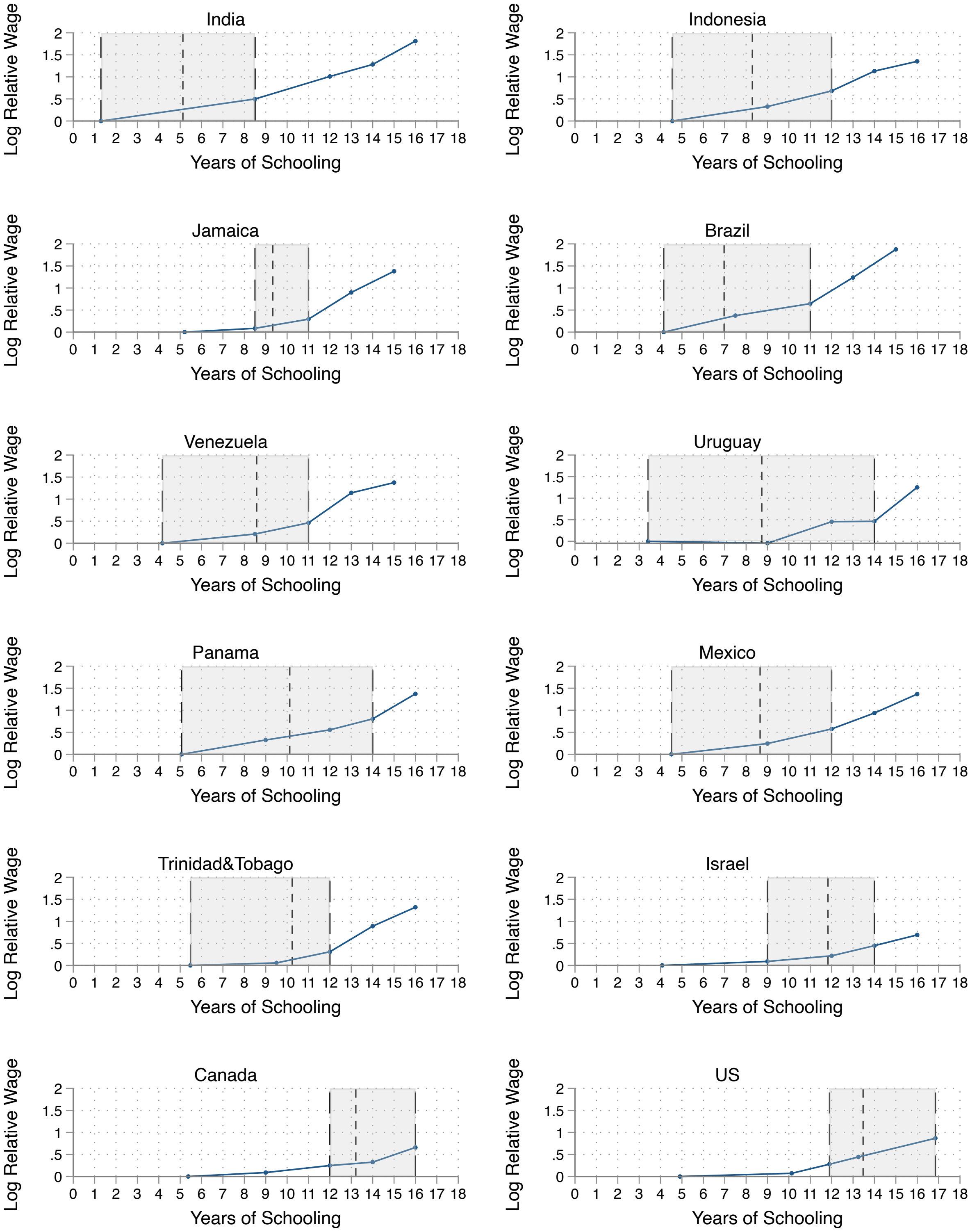
Why do Mincerian returns understate the variation in the skill premium? Figure B.2 illustrates a possible reason. The 12 panels plot, for all countries in the micro-data sample, the estimated log wage gap with respect to primary educated workers against the average years of schooling corresponding to each level of educational attainment. The Mincerian return is the slope of the best linear fit for this relationship. However, for most countries returns to years of education appear to be convex, and particularly low at low levels of educational attainment. As illustrated by the vertical lines in each graph (identifying the 25th percentile, average and 75th percentile of years of schooling in each sample), the sample used for the estimation of Mincerian returns is biased towards low-education workers in poor countries, and towards high-education workers in rich countries. Since low-education workers have relatively low returns, this difference in sample composition tends to reduce the poorer countries' Mincerian returns, therefore understating the cross-country variation in the Mincerian-based skill premium.

Table B.1: Skill Premium and Relative Supply from Mincerian Coefficients

	Caselli, Ponticelli and Rossi (2016)			Montenegro and Patrinos (2014)			IPUMS		
Country	w_H/w_L	$\tilde{H}/\tilde{L}$	$(A_H Q_H)/(A_L Q_L)$	w_H/w_L	$\tilde{H}/\tilde{L}$	$(A_H Q_H)/(A_L Q_L)$	w_H/w_L	$\tilde{H}/\tilde{L}$	$(A_H Q_H)/(A_L Q_L)$
India	1.405	0.210	0.010	1.323	0.191	0.007	1.522	0.236	0.023
Indonesia	1.578	0.077	0.002	1.498	0.073	0.001	1.481	0.073	0.002
Jamaica	3.165	0.095	0.022	1.559	0.081	0.002	1.436	0.079	0.002
Brazil	1.874	0.222	0.026	1.772	0.212	0.019	1.691	0.204	0.023
Venezuela	1.550	0.289	0.025	1.350	0.278	0.015	1.526	0.288	0.034
Uruguay	1.610	0.657	0.142	1.534	0.632	0.112	1.213	0.510	0.054
Panama	1.730	0.419	0.072	1.623	0.403	0.054	1.542	0.389	0.064
Mexico	1.571	0.266	0.022	1.649	0.277	0.027	1.494	0.254	0.025
Trinidad and Tobago	-	-	-	-	-	-	1.326	0.123	0.004
Israel	1.623	0.688	0.160	-	-	-	1.259	0.658	0.100
Canada	1.428	1.772	0.721	1.623	1.796	1.073	1.323	1.756	0.824
United States	1.838	1.428	1	1.847	1.427	1	1.587	1.472	1
Elasticity wrt GDP p.w.	-0.018	0.949	1.842	0.079	1.033	2.303	-0.035	0.901	1.697
	[0.082]	[0.198]	[0.317]	[0.032]	[0.224]	[0.423]	[0.035]	[0.244]	[0.504]

Notes: The Table shows the skill premium, relative skill supply and relative skill efficiency based on country-specific estimates of the Mincerian coefficient, across the countries in the micro-data sample. The column headings indicate the source of the Mincerian coefficients, with *IPUMS* referring to estimates from the same IPUMS and IPUMS International samples used for the main analysis of the paper. The last row shows the coefficient of a regression of the log of each variable on log GDP per worker (standard errors in brackets).

Figure B.2: Returns to Education and Years of Schooling



Notes: The figure plots for all countries in the micro-data sample the average log wage (normalised by the average log wage of primary educated workers) by education groups agains the average years of schooling in each group. The vertical lines identify the average (solid line), 25th percentile (left dashed line) and 75th percentile (right dashed line) of years of schooling for the workers in the wage regression sample. For this calculation, workers are assigned the average years of schooling of their educational group. The graphs are ordered (left to right, up to bottom) by the country's GDP per worker.

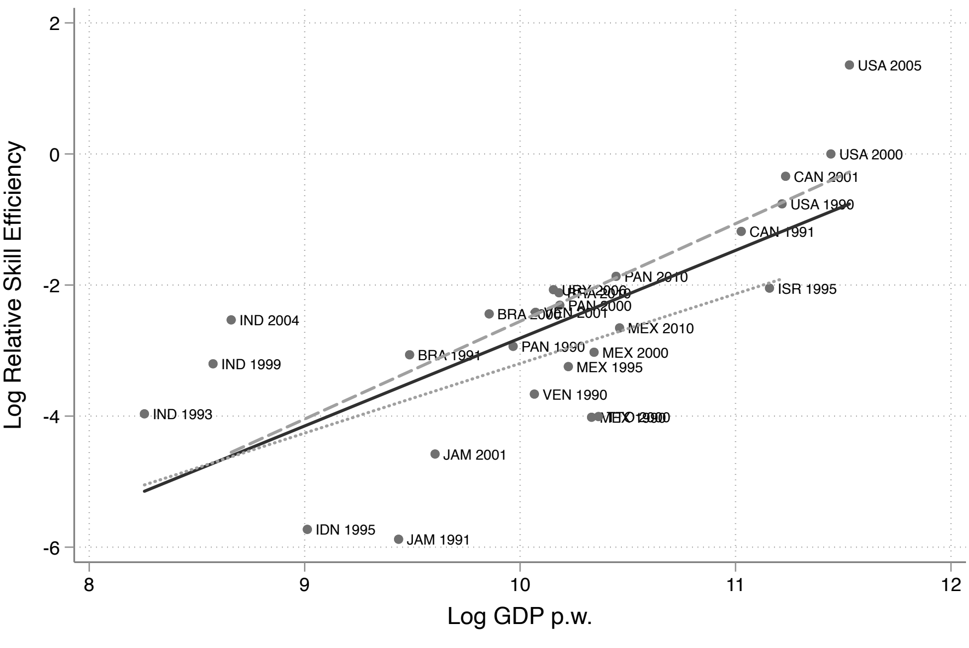
B.5.2 Alternative Definitions of High-Skill

The classification into the high- and low-skill groups is inevitably somewhat arbitrary. While part of macro-development literature has considered secondary educated workers high-skill (Caselli and Coleman, 2006), in labor economics the contrapposition is often cast in terms of high-school and college graduates. Columns (9) and (10) of Table B.3 show the results for two alternative skill thresholds: upper secondary and completed tertiary.[4] Cross-country gaps in relative supply are larger the more comprehensive the definition of high-skill is; as a result, the cross-country variation relative skill efficiency is larger when considering high school graduates as high-skill, and smaller when restricting the high-skill group to college graduates. Even in the latter case, the gaps between the United States and the poorer countries in the sample remain substantial.

B.5.3 Results for All Cross-Sections

Figure B.3 displays log relative skill efficiency for all available cross-sections in 1990-2010, against log GDP per worker in the corresponding year. The relationship is positive and strong, with an elasticity of 1.3. The cross-country pattern is quite stable over time, with a slightly higher slope for cross-sections post-2000 (dashed line).

Figure B.3: Relative Skill Efficiency - All Cross Sections (1990-2010)



Notes: The figure plots relative skill efficiency against log GDP per worker, for all cross-sections in the IPUMS data (1990-2010). Relative skill efficiency is normalized to be 1 (0 in log) for the US in 2000. The solid line shows the best linear fit. The dotted (dashed) line shows the best linear fit for cross-sections earlier than or in (later than) 2000.

[4]When the upper secondary educated are included in the high-skill group, I take the lower secondary educated as baseline low-skill workers.

B.5.4 Average Relative Skill Efficiency

This section develops and computes a measure of average relative skill efficiency, which does not require the choice of particular baseline types of low- and high-skill workers. I amend the notation to explicit acknowledge that factor-augmenting technologies and embodied human capital can in principle vary across educational levels within skill groups. Let $A_{H,c,n}$ and $Q_{H,c,n}$ ($A_{L,c,m}$ and $Q_{L,c,m}$) be respectively the level of factor-specific technology and the embodied human capital of high-skill (low-skill) workers belonging to educational group n (m), where $n \in \mathcal{H} = \{\text{some tertiary, tertiary}\}$ ($m \in \mathcal{L} = \{\text{primary, lower secondary, upper secondary}\}$). The human capital aggregator can be written as

$$G\left(\{A_{H,c,n}Q_{H,c,n}\tilde{H}_{c,n}\}_{n\in\mathcal{H}}, \{A_{L,c,m}Q_{L,c,m}\tilde{L}_{c,m}\}_{m\in\mathcal{L}}\right) = $$
$$= \left[\left(\sum_{n\in\mathcal{H}} A_{H,c,n}Q_{H,c,n}\tilde{H}_{c,n}\right)^{\frac{\sigma-1}{\sigma}} + \left(\sum_{m\in\mathcal{L}} A_{L,c,m}Q_{L,c,m}\tilde{L}_{c,m}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$$

The wage ratio between high-skill workers of type n and low-skill workers of type m is given by

$$\frac{w_{H,c,n}}{w_{L,c,m}} = \left(\frac{A_{H,c,n}Q_{H,c,n}}{A_{L,c,m}Q_{L,c,m}}\right)^{\frac{\sigma-1}{\sigma}} \left(\frac{\sum_{i\in\mathcal{H}} \frac{A_{H,c,i}Q_{H,c,i}}{A_{H,c,n}Q_{H,c,n}}\tilde{H}_{c,i}}{\sum_{j\in\mathcal{L}} \frac{A_{L,c,j}Q_{L,c,j}}{A_{L,c,m}Q_{L,c,m}}\tilde{L}_{c,j}}\right)^{-\frac{1}{\sigma}} \tag{11}$$

In the paper I back out $\frac{A_{H,c}Q_{H,c}}{A_{L,c}Q_{L,c}} \equiv \frac{A_{H,c,\text{tertiary}}Q_{H,c,\text{tertiary}}}{A_{L,c,\text{upper secondary}}Q_{L,c,\text{upper secondary}}}$ from (11), using data on $\{w_{H,c,i}\}_{i\in\mathcal{H}}$, $\{w_{L,c,j}\}_{j\in\mathcal{L}}$, $\{\tilde{H}_{c,i}\}_{i\in\mathcal{H}}$, $\{\tilde{L}_{c,j}\}_{j\in\mathcal{L}}$ and the fact that $\frac{w_{H,c,i}}{w_{H,c,n}} = \frac{A_{H,c,i}Q_{H,c,i}}{A_{H,c,n}Q_{H,c,n}}$ and $\frac{w_{L,c,j}}{w_{L,c,m}} = \frac{A_{L,c,j}Q_{L,c,j}}{A_{L,c,m}Q_{L,c,m}}$ for all $i \in \mathcal{H}$ and $j \in \mathcal{L}$. Here, I consider the following measure of average relative skill efficiency,

$$\overline{RSE}_c = \frac{\sum_{n\in\mathcal{H}} A_{H,c,n}Q_{H,c,n}\frac{\tilde{H}_{c,n}}{\sum_{i\in\mathcal{H}}\tilde{H}_{c,i}}}{\sum_{m\in\mathcal{L}} A_{L,c,m}Q_{L,c,m}\frac{\tilde{L}_{c,m}}{\sum_{j\in\mathcal{L}}\tilde{L}_{c,j}}}$$

that is the ratio between weighted averages of the efficiencies of the various educational groups. This measure is obviously affected by the educational composition within skill groups; to assess the importance of this, I also consider an adjusted version where educational shares within skill groups are fixed at the US levels

$$\overline{RSE}_c^{Adj} = \frac{\sum_{n\in\mathcal{H}} A_{H,c,n}Q_{H,c,n}\frac{\tilde{H}_{US,n}}{\sum_{n\in\mathcal{H}}\tilde{H}_{US,n}}}{\sum_{m\in\mathcal{L}} A_{L,c,m}Q_{L,c,m}\frac{\tilde{L}_{US,m}}{\sum_{m\in\mathcal{L}}\tilde{L}_{US,m}}}$$

Both $\overline{RSE}_c$ and $\overline{RSE}_c^{Adj}$ can be easily computed using data on wages and educational shares. In particular, notice that one can write

$$\overline{RSE}_c = \left(\frac{\bar{w}_{H,c}}{\bar{w}_{L,c}}\right)^{\frac{\sigma}{\sigma-1}} \left(\frac{\sum_{n\in\mathcal{H}}\tilde{H}_{c,n}}{\sum_{m\in\mathcal{L}}\tilde{L}_{c,m}}\right)^{\frac{1}{\sigma-1}}$$

$$\overline{RSE}_c^{Adj} = \frac{\bar{w}_{H,c}^{Adj}}{\bar{w}_{L,c}^{Adj}}\left(\frac{\bar{w}_{H,c}}{\bar{w}_{L,c}}\right)^{\frac{1}{\sigma-1}} \left(\frac{\sum_{n\in\mathcal{H}}\tilde{H}_{c,n}}{\sum_{m\in\mathcal{L}}\tilde{L}_{c,m}}\right)^{\frac{1}{\sigma-1}} = \frac{\bar{w}_{H,c}^{Adj}}{\bar{w}_{L,c}^{Adj}}\left(\overline{RSE}_c\frac{\sum_{n\in\mathcal{H}}\tilde{H}_{c,n}}{\sum_{m\in\mathcal{L}}\tilde{L}_{c,m}}\right)^{\frac{1}{\sigma}}$$

where $\bar{w}_{H,c}$ and $\bar{w}_{L,c}$ are weighted averages of the wages across all educational groups,

$$\bar{w}_{H,c} = \sum_{n \in \mathcal{H}} w_{H,c,n} \frac{\tilde{H}_{c,n}}{\sum_{i \in \mathcal{H}} \tilde{H}_{c,i}}$$
$$\bar{w}_{L,c} = \sum_{m \in \mathcal{L}} w_{L,c,m} \frac{\tilde{L}_{c,m}}{\sum_{j \in \mathcal{L}} \tilde{L}_{c,j}}$$

and $\bar{w}_{H,c}^{Adj}$ and $\bar{w}_{L,c}^{Adj}$ are the composition-adjusted counterparts

$$\bar{w}_{H,c}^{Adj} = \sum_{n \in \mathcal{H}} w_{H,c,n} \frac{\tilde{H}_{US,n}}{\sum_{i \in \mathcal{H}} \tilde{H}_{US,i}}$$
$$\bar{w}_{L,c}^{Adj} = \sum_{m \in \mathcal{L}} w_{L,c,m} \frac{\tilde{L}_{US,m}}{\sum_{j \in \mathcal{L}} \tilde{L}_{US,j}}$$

Table B.2 displays the resulting $\overline{RSE}_c$ and $\overline{RSE}_c^{Adj}$. For both measures, the country-specific estimates and the elasticities with respect to GDP per worker are close to the baseline relative skill efficiency shown in Table I of the paper. This reflects the fact that the baseline groups used in the paper (tertiary educated for the high-skilled, upper secondary educated for the low-skilled) are not atypical in terms of the cross-country variation in relative skill efficiency (and also relatively large across all countries, meaning that they drive a significant part of the variation in average relative skill efficiency). The composition-adjusted measures varies slightly more between rich and poor countries, as poor countries are relatively more abundant in low-educated workers within the low-skill group.

Table B.2: Average Relative Skill Efficiency

Country	$\overline{RSE}$	$\overline{RSE}^{Adj}$
India	0.083	0.042
Indonesia	0.005	0.004
Jamaica	0.012	0.010
Brazil	0.133	0.082
Venezuela	0.108	0.099
Uruguay	0.128	0.115
Panama	0.131	0.096
Mexico	0.075	0.050
Trinidad and Tobago	0.018	0.018
Israel	0.145	0.138
Canada	0.757	0.733
United States	1	1
Elasticity wrt GDP p.w.	1.199	1.401
	[0.413]	[0.387]

Notes: The Table shows the two measures of average relative skill efficiency defined in the text across the countries in the micro-data sample. Both measures are normalised such that they take value 1 for the United States. The last row shows the coefficient of a regression of the log of each variable on log GDP per worker (standard errors in brackets).

B.6 Country-Level Results

Table B.3 presents the country-level results on relative skill efficiency. The first column reports the baseline results from Table I in the paper, while the additional columns cover all the robustness exercises discussed in Section II.C, as well as the additional ones described in this Appendix.

Table B.3: Relative Skill Efficiency - Country-Level Results

	$(A_H Q_H) / (A_L Q_L)$										
	Baseline (1)	Gender & Experience (2)	Self-Employed (3)	Agriculture (4)	Manufacturing (5)	Low-Skill Services (6)	High-Skill Services (7)	Sec Comp Counterfactual (8)	Threshold: Upper Sec (9)	Threshold: Tertiary (10)	Net of KH Compl (11)
India	0.041	0.028	-	0.003	0.029	0.035	0.344	0.059	0.004	0.177	0.149
Indonesia	0.003	0.003	-	0.3×10^{-3}	0.007	0.003	0.055	0.006	0.001	0.009	0.019
Jamaica	0.010	0.010	-	0.5×10^{-3}	0.012	0.006	0.075	0.013	0.009	0.058	0.160
Brazil	0.087	0.084	0.088	0.003	0.048	0.030	0.391	0.087	0.010	0.513	0.133
Venezuela	0.089	0.071	0.088	0.004	0.080	0.029	0.421	0.088	0.009	0.8×10^{-4}	0.186
Uruguay	0.126	0.121	-	0.040	0.099	0.052	0.361	0.130	0.007	0.121	0.101
Panama	0.099	0.095	0.132	0.003	0.034	0.083	0.397	0.108	0.010	0.420	0.154
Mexico	0.049	0.045	0.052	0.002	0.031	0.028	0.251	0.052	0.004	0.318	0.064
Trinidad and Tobago	0.018	0.016	0.019	0.002	0.021	0.016	0.052	0.019	0.028	0.034	0.073
Israel	0.129	0.106	0.124	0.015	0.075	0.026	0.386	0.121	0.047	0.325	0.149
Canada	0.711	0.884	0.729	0.101	0.208	0.225	1.935	0.734	0.099	0.541	0.608
United States	1	1	1	0.133	0.301	0.317	2.654	1	1	1	1
θ_AQ	1.408	1.520	1.533	1.719	0.952	0.992	0.850	1.236	1.682	0.975	0.727
	[0.394]	[0.398]	[0.639]	[0.466]	[0.265]	[0.359]	[0.360]	[0.385]	[0.361]	[0.903]	[0.292]

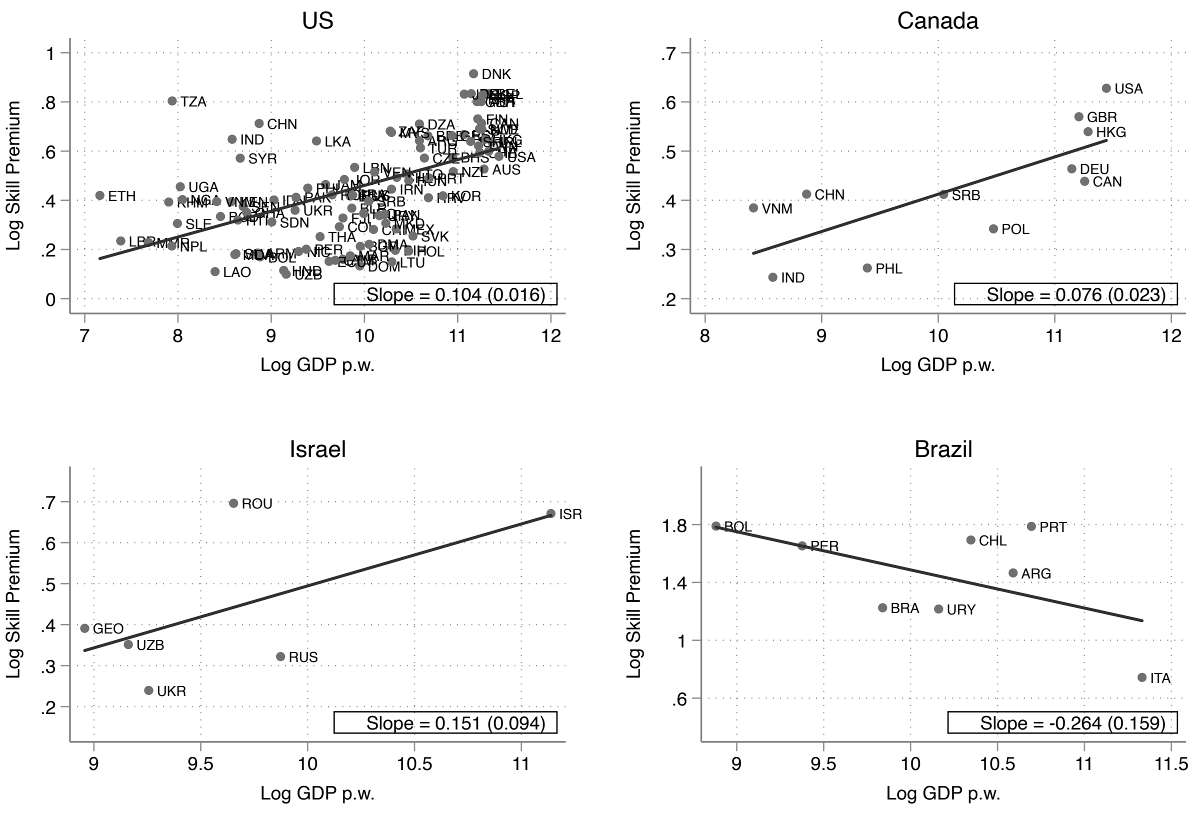
Notes: The Table shows the relative skill efficiency across the countries in the micro-data sample. The first column reports the baseline results, while other columns correspond to different robustness checks, as indicated in the column headings. Relative skill efficiency is normalised such that it takes value 1 for the United States; for the sector-level measures (columns 4-7), the normalisation is at the aggregate level, so that the magnitudes are comparable to each other. The last row show the coefficient of a regression of the log of each variable and log GDP per capita (standard errors in brackets).

C Interpreting Relative Skill Efficiency: Additional Material

C.1 Skill Premia across All Host Countries

Figure C.1 reports the skill premium by country of origin against GDP per worker for all host countries in the sample. It is evident that the data for host countries different from the US have a much smaller sample size in terms of origin countries, spanning a more limited part of the GDP distribution. Within Canada and Israel skill premia are mildly increasing in the GDP of the country of education, with slopes respectively slightly lower (0.076) and higher (0.151) than the US one (0.104). Within Brazil, the estimate of slope is negative, with a large standard error. While obviously these patterns are more subject to the impact of single observations - which might be noisy, or, in the language of equation (17) in the paper, characterized by sizeable $\log\left(\varepsilon^a_{H,c}/\varepsilon^a_{L,c}\right)$ terms - none of them is consistent with a sensibly larger estimate of θ_Q. Indeed, the estimate pooling all host countries (row 2 of Table III) is similar to the one from the US.

Figure C.1: Skill Premia by Host Country



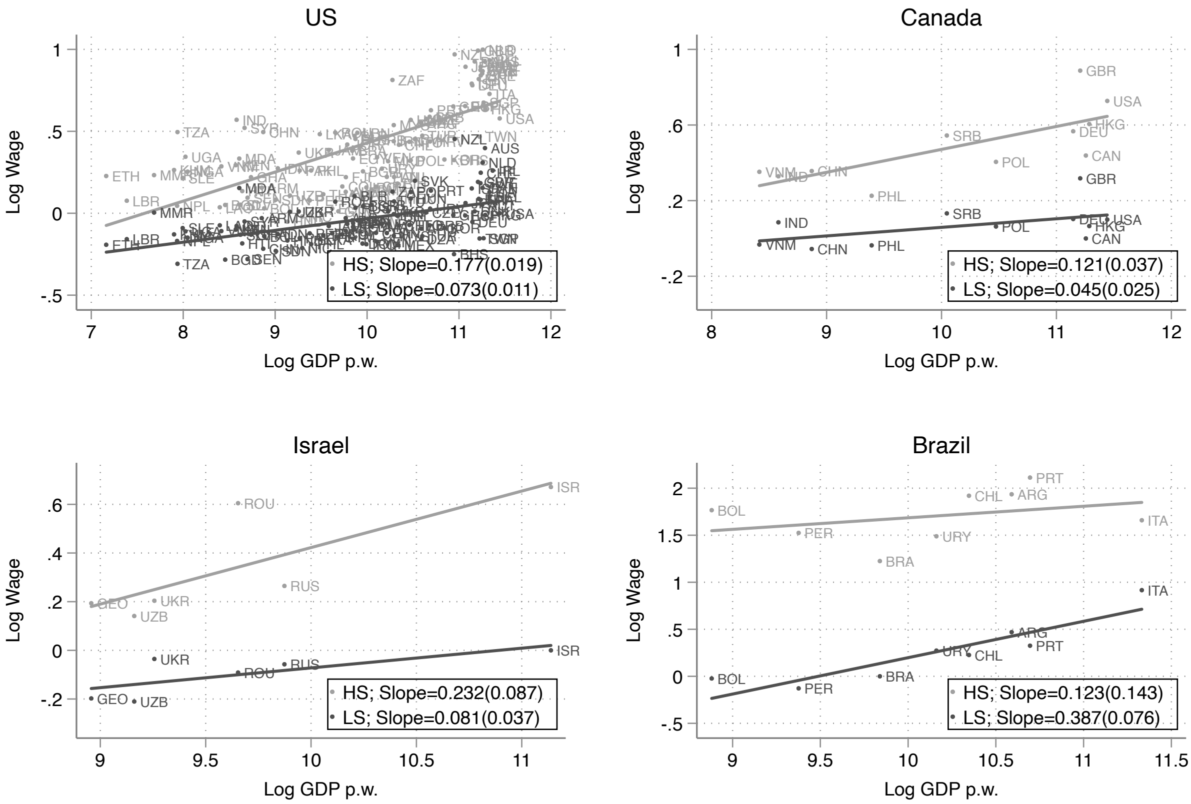
Notes: The figure plots for all host countries the log skill premium across immigrants' countries of origin, against the log GDP per worker in the country of origin. The solid line shows the best linear fit.

Figure C.2 displays the underlying wage levels for low- and high-skill workers, as well as their elasticities with respect to GDP per worker (for each host country, the difference between the high- and low-skill elasticities obviously gives the skill premium elasticity displayed in Figure C.1).[5] For all host countries and skill levels, wages increase with respect to GDP per worker in the country of origin.

[5]Log wages by country of origin and education are constructed as predicted values from the same wage regression used to construct skill premia, with the years since migration controls centered around their sample average.

The slopes are of comparable magnitudes across host countries; the only exception is represented by low-skill wages in Brazil that increase faster with development (leading to the downward slope for the skill premium in Figure C.1). Notice that a low-skill wage elasticity in line with the other host countries (or even of 0) would still imply within Brazil skill premia consistent with a low θ_Q.

Figure C.2: High- and Low-Skill Wages by Host Country



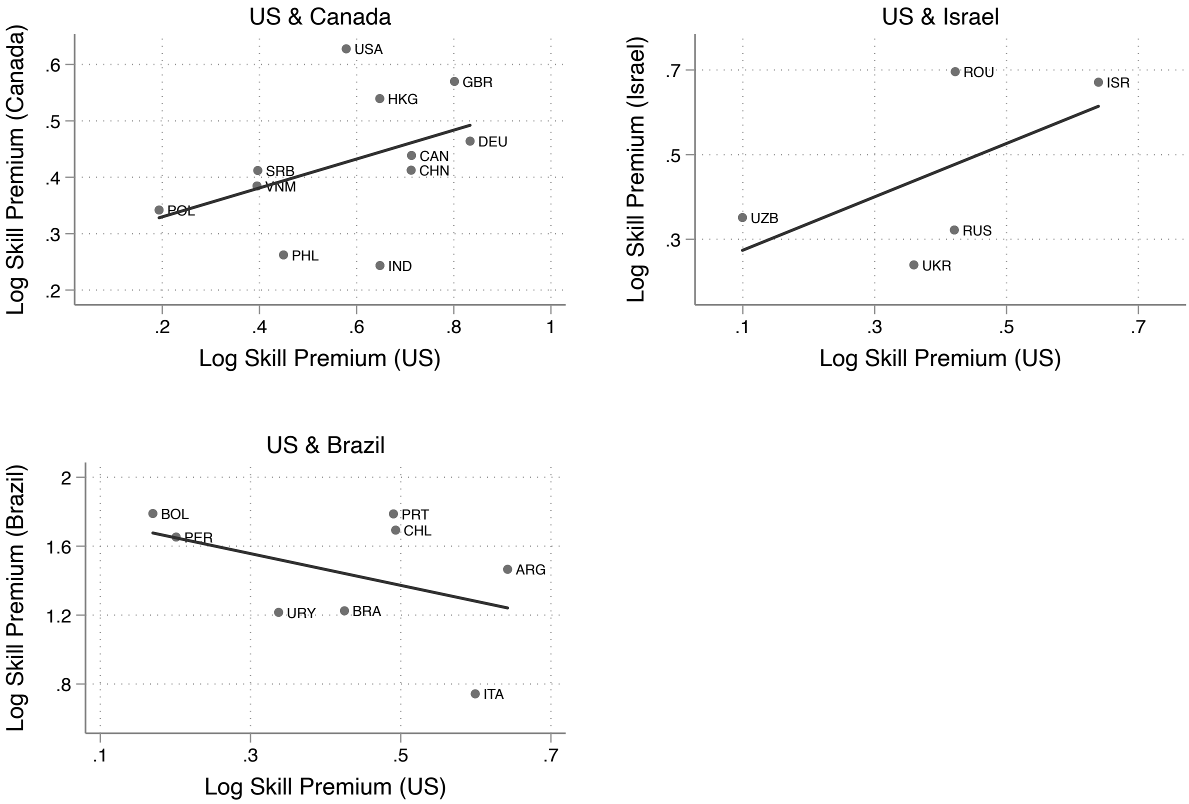
Notes: The figure plots for all host countries the log wage of high- and low-skill workers across countries of origin, against the log GDP per worker in the country of origin. In each plot, wages are normalized to 1 (0 in log) for low-skill natives. The solid line shows the best linear fit (slope reported in each plot, with standard errors in parentheses).

Figure C.3 compares the skill premia across the US and the other host countries, for the overlapping countries of origin. In light of Figure C.1 and Figure C.2, it is not surprising that the correlation is positive for Canada and Israel, and negative for Brazil. The comparisons in Figure C.3 highlight that the pair-specific term in equation (17) does vary substantially across some pairs of host and origin countries; for example, higly-educated Bolivian and Peruvian workers appear, relative to the low-educated from the same country of origin, more productive in Brazil than in the US, while the opposite is true for Italians. This might be due to idiosyncratic patterns of differential selection or barriers to skill utilization, which (if not averaging out across host countries) would introduce noise in the estimates of relative human capital.[6] As discussed in the paper, the key question for the purpose of estimating θ_Q is whether the pair-specific term correlates with GDP per worker in the country of origin, and in particular whether a strong negative correlation might be responsible for the low estimate of θ_Q. The evidence provided in Section IV suggests that this is not the case within the US,

[6]For example, the low wages for low-skill Bolivian and Peruvian immigrants in Brazil displayed in Figure C.2 might be connected to the large flows of illegal immigrants from these countries, plausibly facing a variety of barriers in the Brazilian labor market.

the largest host country in my sample.

Figure C.3: Skill Premia across Host Country Pairs

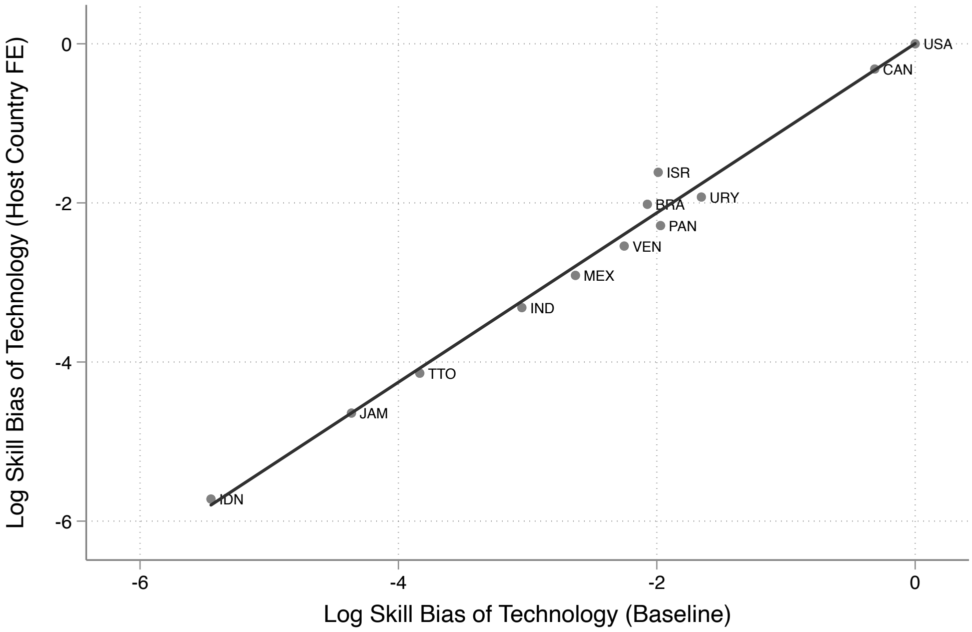


Notes: The figure plots the log skill premium across pairs of host countries for all the overlapping countries of origin. The solid line shows the best linear fit.

C.2 Skill Bias Estimates

Figure C.4 compares two sets of estimates of the skill bias of technology. One is obtained from equation 8 in the paper, given the estimate of relative human capital from Section III. The other is computed from the estimated host country fixed effects, as illustrated in Section III. The difference between the two consists in the wage moments they use; the former is based on cross-country differences in natives' skill premia, while the latter on differences in skill premia across host countries for given countries of origin. The estimates are extremely similar to each other; indeed, the cross-country variation in skill bias is mostly driven by the relative skill supply, which enters symmetrically in the two measures.

Figure C.4: Alternative Estimates of Skill Bias



Notes: The figure plots the two alternative estimates of technology skill bias described in the text. Both measures are normalized to be 0 for the US. The solid line shows the best linear fit.

C.3 Different Production Technologies

C.3.1 Capital-Skill Complementarity

This section illustrates how equation (18) in the paper is affected by capital-skill complementarity. Let the production function in country c be

$$Y_c = F_c \left(K_c^S, \left[(A_{L,c} L_c)^{\frac{\sigma-1}{\sigma}} + \left[(A_{H,c} H_c)^{\frac{\eta-1}{\eta}} + \left(A_{K,c} K_c^E \right)^{\frac{\eta-1}{\eta}} \right]^{\frac{\sigma-1}{\sigma} \frac{\eta}{\eta-1}} \right]^{\frac{\sigma}{\sigma-1}} \right)$$

where

$$H_c = \sum_a Q_{H,a}\varepsilon^a_{H,c}\tilde{H}^a_c$$
$$L_c = \sum_a Q_{H,a}\varepsilon^a_{H,c}\tilde{H}^a_c$$

The skill premium for workers educated in country a and employed in country c is

$$\log\frac{w^a_{H,c}}{w^a_{L,c}} = \underbrace{\log\left[\left(1+\left(\frac{A_{K,c}K^E_c}{A_{H,c}Q_{H,c}\tilde{H}_c}\right)^{\frac{\eta-1}{\eta}}\right)^{\frac{\sigma-\eta}{\sigma(\eta-1)}}\left(\frac{A_H}{A_L}\right)^{\frac{\sigma-1}{\sigma}}\left(\frac{Q_{H,c}\tilde{H}_c}{Q_{L,c}\tilde{L}_c}\right)^{-\frac{1}{\sigma}}\right]}_{\text{Country } c \text{ FE}} + \underbrace{\log\frac{Q_{H,a}}{Q_{L,a}}}_{\text{Country } a \text{ FE}} + \underbrace{\log\frac{\varepsilon^a_{H,c}}{\varepsilon^a_{L,c}}}_{\text{Pair-Specific Term}}$$

where $\tilde{H}_c = \sum_a (Q_{H,a}/Q_{H,c})\varepsilon^a_{H,c}\tilde{H}^a_c$ and $\tilde{L}_c = \sum_a (Q_{L,a}/Q_{L,c})\varepsilon^a_{L,c}\tilde{L}^a_c$.

C.3.2 Division of Labor

Consider the production technology discussed in Appendix B.4,

$$Y_c = A_c F\left[A_{K,c}K_c, \left((A_{H,c}H_c)^{\frac{\sigma-1}{\sigma}} + (A_{L,c}L_c)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}\right]$$

where

$$H_c = \left[\sum_{j=1}^{N_c}\left(\frac{f_c(N_c)}{d_c(N_c)}\sum_a Q_{H,a}\varepsilon^a_{H,c}\tilde{H}^a_{j,c}\right)^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}$$
$$L_c = \sum_a Q_{L,a}\varepsilon^a_{L,c}\tilde{L}^a_c$$

where $\tilde{H}^a_{j,c}$ is the number of workers from a in occupation j and country c. Notice that the $\varepsilon^a_{H,c}$ term can in principle capture any skill loss associated to differences in the organization of production between country a and country c; for example, if migrants are in fact stuck with the productivity gain from specialization acquired in their country of origin, $f_a(N_a)$, then $\varepsilon^a_{H,c} = f_a(N_a)/f_c(N_c)$.[7] If $\eta < \infty$, the equalization of the wage per efficiency unit across occupations implies for each i

$$\sum_a Q_{H,a}\varepsilon^a_{H,c}\tilde{H}^a_{i,c} = \frac{1}{N_c}\sum_{j=1}^{N_c}\sum_a Q_{H,a}\varepsilon^a_{H,c}\tilde{H}^a_{j,c}$$

The skill premium for workers educated in country a and employed in country c is

$$\log\frac{w^a_{H,c}}{w^a_{L,c}} = \underbrace{\log\left[\left(\frac{A_{H,c}}{A_{L,c}}N_c^{\frac{1}{\eta-1}}\frac{f_c(N_c)}{d_c(N_c)}\right)^{\frac{\sigma-1}{\sigma}}\left(\frac{Q_{H,c}\tilde{H}_c}{Q_{L,c}\tilde{L}_c}\right)^{-\frac{1}{\sigma}}\right]}_{\text{Country } c \text{ FE}} + \underbrace{\log\frac{Q_{H,a}}{Q_{L,a}}}_{\text{Country } a \text{ FE}} + \underbrace{\log\frac{\varepsilon^a_{H,c}}{\varepsilon^a_{L,c}}}_{\text{Pair-Specific Term}}$$

[7] If the skill loss is large enough, high-skill migrants might prefer to work in the low-skill sector. This possibility is investigated empirically in Section IV.B of the paper.

where $\tilde{H}_c = \sum_a (Q_{H,a}/Q_{H,c})\varepsilon^a_{H,c}\tilde{H}^a_c$ and $\tilde{L}_c = \sum_a (Q_{L,a}/Q_{L,c})\varepsilon^a_{L,c}\tilde{L}^a_c$.

D Development Accounting: Additional Material

D.1 Counterfactual GDP Ratio Derivation

Equation (27) can be derived as follows. Write y^*_P as

$$y^*_P = Z_P A_{L,P} Q_{L,R}\tilde{L}_R \left[1 + \left(\frac{A_{H,P}Q_{H,R}\tilde{H}_R}{A_{L,P}Q_{L,R}\tilde{L}_R}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$$

Dividing by y_P,

$$\frac{y^*_P}{y_P} = \frac{Q_{L,R}\tilde{L}_R}{Q_{L,P}\tilde{L}_P}\left[\frac{1 + \left(\frac{A_{H,P}Q_{H,R}\tilde{H}_R}{A_{L,P}Q_{L,R}\tilde{L}_R}\right)^{\frac{\sigma-1}{\sigma}}}{1 + \left(\frac{A_{H,P}Q_{H,P}\tilde{H}_P}{A_{L,P}Q_{L,P}\tilde{L}_P}\right)^{\frac{\sigma-1}{\sigma}}}\right]^{\frac{\sigma}{\sigma-1}}$$

Substituting in the skill premia,

$$\frac{y^*_P}{y_P} = \frac{Q_{L,R}\tilde{L}_R}{Q_{L,P}\tilde{L}_P}\left[\frac{1 + \frac{w_{H,P}H_P}{w_{L,P}L_P}\left(\frac{Q_{H,R}/Q_{L,R}}{Q_{H,P}/Q_{L,P}}\right)^{\frac{\sigma-1}{\sigma}}\left(\frac{\tilde{H}_R/\tilde{L}_R}{\tilde{H}_P/\tilde{L}_P}\right)^{\frac{\sigma-1}{\sigma}}}{1 + \frac{w_{H,P}H_P}{w_{L,P}L_P}}\right]^{\frac{\sigma}{\sigma-1}}$$

Dividing both sides by y_R/y_P and replacing $\frac{Q_{H,R}/Q_{L,R}}{Q_{H,P}/Q_{L,P}}$ with $\left(\frac{y_R}{y_P}\right)^{\theta_Q}$ gives equation (27).

D.2 Extending Caselli and Ciccone (2013)

This Appendix extends the theoretical results in Caselli and Ciccone (2013) to the case where the human capital endowment of high- and low-skill labor varies across countries. Let the GDP per worker for country c be $y_c = f_c(Q_{L,c}\tilde{L}_c, Q_{H,c}\tilde{H}_c)$, where

$$f_c\left(Q_L\tilde{L}, Q_H\tilde{H}\right) = Z_c A_{L,c} Q_L\tilde{L}\left[1 + \left(\frac{A_{H,c}Q_H\tilde{H}}{A_{L,c}Q_L\tilde{L}}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$$

The counterfactual y^*_P defined in Section V can be written as $y^*_P = f_P(Q_{L,R}\tilde{L}_R, Q_{H,R}\tilde{H}_R)$. From the concavity of $f_P(.)$, it follows that

$$y^*_P - y_P \leqslant f_{L,P} \times \left(Q_{L,R}\tilde{L}_R - Q_{L,P}\tilde{L}_P\right) + f_{H,P} \times \left(Q_{H,R}\tilde{H}_R - Q_{H,P}\tilde{H}_P\right)$$

where $f_{S,P} = \frac{\partial}{\partial Q_{S,P}\tilde{S}_P} f_P\left(Q_{L,P}\tilde{L}_P, Q_{H,P}\tilde{H}_P\right)$, for $S = \{L, H\}$. Substituting for $f_{L,P}$ and $f_{H,P}$ and dividing by y_P, we obtain

$$\frac{y_P^* - y_P}{y_P} \leqslant \frac{A_{L,P}^{\frac{\sigma-1}{\sigma}}\left(Q_{L,P}\tilde{L}_P\right)^{-\frac{1}{\sigma}}\left(Q_{L,R}\tilde{L}_R - Q_{L,P}\tilde{L}_P\right) + A_{H,P}^{\frac{\sigma-1}{\sigma}}\left(Q_{H,P}\tilde{H}_P\right)^{-\frac{1}{\sigma}}\left(Q_{H,R}\tilde{H}_R - Q_{H,P}\tilde{H}_P\right)}{\left(A_{L,P}Q_{L,P}\tilde{L}_P\right)^{\frac{\sigma-1}{\sigma}} + \left(A_{H,P}Q_{H,P}\tilde{H}_P\right)^{\frac{\sigma-1}{\sigma}}}$$

$$\frac{y_P^*}{y_P} \leqslant \frac{A_{L,P}^{\frac{\sigma-1}{\sigma}}\left(Q_{L,P}\tilde{L}_P\right)^{-\frac{1}{\sigma}} Q_{L,R}\tilde{L}_R + A_{H,P}^{\frac{\sigma-1}{\sigma}}\left(Q_{H,P}\tilde{H}_P\right)^{-\frac{1}{\sigma}} Q_{H,R}\tilde{H}_R}{\left(A_{L,P}Q_{L,P}\tilde{L}_P\right)^{\frac{\sigma-1}{\sigma}} + \left(A_{H,P}Q_{H,P}\tilde{H}_P\right)^{\frac{\sigma-1}{\sigma}}}$$

$$\frac{y_P^*}{y_P} \leqslant \frac{Q_{L,R}\tilde{L}_R}{Q_{L,P}\tilde{L}_P}\left[\frac{1 + \left(\frac{A_{H,P}Q_{H,P}\tilde{H}_P}{A_{L,P}Q_{L,P}\tilde{L}_P}\right)^{\frac{\sigma-1}{\sigma}} \frac{Q_{H,R}/Q_{L,R}}{Q_{H,P}/Q_{L,P}} \frac{\tilde{H}_R/\tilde{L}_R}{\tilde{H}_P/\tilde{L}_P}}{1 + \left(\frac{A_{H,P}Q_{H,P}\tilde{H}_P}{A_{L,P}Q_{L,P}\tilde{L}_P}\right)^{\frac{\sigma-1}{\sigma}}}\right]$$

$$\frac{y_P^*}{y_P} \leqslant \frac{Q_{L,R}\tilde{L}_R}{Q_{L,P}\tilde{L}_P}\left[\frac{1 + \frac{w_{H,P}H_P}{w_{L,P}L_P}\left(\frac{y_R}{y_P}\right)^{\theta_Q}\left(\frac{\tilde{H}_R/\tilde{L}_R}{\tilde{H}_P/\tilde{L}_P}\right)}{1 + \frac{w_{H,P}H_P}{w_{L,P}L_P}}\right]$$

$$\frac{y_P^*}{y_R} \leqslant \frac{Q_{L,R}\tilde{L}_R}{Q_{L,P}\tilde{L}_P}\left[\frac{1 + \frac{w_{H,P}H_P}{w_{L,P}L_P}\left(\frac{y_R}{y_P}\right)^{\theta_Q}\left(\frac{\tilde{H}_R/\tilde{L}_R}{\tilde{H}_P/\tilde{L}_P}\right)}{1 + \frac{w_{H,P}H_P}{w_{L,P}L_P}}\right] \Bigg/ \frac{y_R}{y_P}$$

where the right hand side corresponds to equation (27) in the paper for $\sigma = \infty$. In other words, for any given θ_Q, the counterfactual ratio computed assuming imperfect substitutability represents an upper bound.

D.3 Alternative Formulations

Table D.1 illustrates the results from alternative specifications of the development accounting exercise considered in Section V. The left panel displays the counterfactual ratio y_P^*/y_R resulting from the three calibration strategies discussed in the paper and different thresholds for the classification of high-skill workers.[8] As noticed in Hendricks and Schoellman (2020), the results from Jones (2014a)'s calibration are quite sensitive to the chosen threshold, with broader definitions of high-skill labor leading to larger effects of equalizing relative human capital, as well as a larger amplification from imperfect substitutability. On the other hand, when relative human capital is estimated from migrants' skill premia, the counterfactual ratio is stable across different definitions of high-skill labor, and marginally lower for lower values of σ. Results are very similar when relative human capital is assumed to be constant, as in Caselli and Ciccone (2019).

For completeness, the right panel shows the results from an alternative thought experiment, where the rich country is assigned the relative human capital of the poor country. In particular, I define

$$y_R^* = Z_R A_{L,R} Q_{L,P}\tilde{L}_P\left[1 + \left(\frac{A_{H,R}Q_{H,P}\tilde{H}_P}{A_{R,P}Q_{L,P}\tilde{L}_P}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$$

[8]In row (7), I take lower secondary educated as baseline low-skill workers, and (for the migrant-based calibration) use the corresponding estimate for relative human capital. The resulting implied elasticity for India and the US is $\theta_Q = 0.064$, very similar to the baseline one.

and calculate the corresponding counterfactual ratio from

$$\frac{y_P}{y_R^*} = \frac{Q_{L,R}\tilde{L}_R}{Q_{L,P}\tilde{L}_P}\left[\frac{1+\frac{w_{H,R}H_R}{w_{L,R}L_R}}{1+\frac{w_{H,R}H_R}{w_{L,R}L_R}\left(\frac{y_P}{y_R}\right)^{\frac{\sigma-1}{\sigma}\theta_Q}\left(\frac{\tilde{H}_P/\tilde{L}_P}{\tilde{H}_R/\tilde{L}_R}\right)^{\frac{\sigma-1}{\sigma}}}\right]^{\frac{\sigma}{\sigma-1}} \Bigg/ \frac{y_R}{y_P}$$

In absence of cross-country differences in factor-specific technology, as implied by Jones (2014a)'s calibration, y_P/y_R^* is identical to y_P^*/y_R; however, the two experiments are conceptually different when relatively skill efficiency does not reflect only relative human capital. Across all definitions of high-skill labor, the migrant-based calibration with $\sigma = 1.5$ implies a substantially lower y_P/y_R^* compared to when $\theta_Q = \theta_{AQ}$ (though the difference is less pronounced when only workers with completed tertiary education are considered as high-skilled). For $\theta_Q = 0$, y_P/y_R^* is generally higher than y_P^*/y_R; setting θ_Q as implied by the migrant-based estimates increases y_P/y_R^* only marginally. The impact of σ is somewhat different in this thought experiment, as, for a given θ_Q, assuming a lower σ necessarily increases the counterfactual ratio.[9] However, the effect of σ in the migrant-based calibration is much milder compared to Jones (2014a)'s calibration, where a lower σ also dramatically increases the inferred gap in relative human capital.

Table D.1: Relative Human Capital and Development Accounting - Alternative Formulations

	y_P^*/y_R				y_P/y_R^*			
	$\sigma = 1.5$	$\sigma = 2$	$\sigma = 4$	$\sigma = \infty$	$\sigma = 1.5$	$\sigma = 2$	$\sigma = 4$	$\sigma = \infty$
Relative Human Capital Interpretation								
(1) Upper Secondary	8.845	0.883	0.190	0.088	8.845	0.883	0.190	0.088
(2) Some Tertiary	0.698	0.289	0.161	0.120	0.698	0.289	0.161	0.120
(3) Tertiary	0.219	0.162	0.132	0.120	0.219	0.162	0.132	0.120
Relative Technology Interpretation								
(4) Upper Secondary	0.076	0.094	0.121	0.145	0.214	0.190	0.148	0.109
(5) Some Tertiary	0.104	0.112	0.126	0.140	0.171	0.159	0.142	0.127
(6) Tertiary	0.119	0.122	0.127	0.132	0.138	0.134	0.129	0.125
Migrant-Based Calibration								
(7) Upper Secondary	0.087	0.109	0.143	0.173	0.249	0.217	0.164	0.115
(8) Some Tertiary	0.112	0.123	0.140	0.158	0.187	0.172	0.150	0.133
(9) Tertiary	0.125	0.129	0.135	0.142	0.145	0.140	0.134	0.128

Notes: The Table shows the counterfactual GDP ratios y_P^*/y_R and y_P/y_R^*, where P is India and R is the US, under different calibrations of the elasticity of relative human capital θ_Q and different thresholds for the definition of high-skill workers. For comparison, the actual GDP ratio in the data is $y_P/y_R = 0.057$.

[9]This can be shown analytically by defining $y_R^* = f_R(Q_{L,P}\tilde{L}_P, Q_{H,P}\tilde{H}_P)$, following the derivation of Section D.2 and inverting the resulting inequality.

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