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

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Abstract

I study how the relative efficiency of high- and low-skill labor varies across countries. Using micro data for countries at different stages of development, I document that differences in relative quantities and wages are consistent with high-skill workers being relatively more productive in rich countries. I exploit variation in the skill premia of foreign-educated migrants to discriminate between two possible drivers of this pattern: cross-country differences in the skill bias of technology and in the relative human capital of skilled labor. I find that the former is quantitatively more important, and discuss the implications of this result for development accounting.

JEL Classification: O11, O47, I25, E24

A question of major interest in macroeconomics is how the structure of production varies across countries. The traditional view is that rich and poor countries are set apart by large differences in a factor-neutral productivity shifter, while gaps in the relative amount and productivity of various factors of production are of more limited importance (Hall and Jones, 1999). Recently, this view has been challenged, owing both to improved measurements of production inputs (Schoellman, 2012; Lagakos et al., 2016) and richer characterizations of the production technology (Jones, 2014a; Caselli, 2016).

An emerging view in this line of research is that the relative efficiency of high- and low-skill workers varies substantially across countries (Caselli and Coleman, 2006; Caselli, 2016;

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Malmberg, 2018). This conclusion typically follows from the analysis of quantities and prices. In a world with imperfect substitutability, a higher relative supply of skilled labor should be reflected in a lower relative price. However, existing estimates for the skill premium display limited variability across countries, despite large gaps in enrollment rates and educational achievements. This suggests that high-skill workers are, in relative terms, much more productive in rich (and skill-abundant) countries, attenuating the downward pressure on the skill premium stemming from their high supply.

Two broad interpretations have been proposed to explain this pattern. On one hand, the productive environment in rich and poor countries might be differentially complementary to high- and low-skill workers (the "relative technology" interpretation). This might be because firms in rich countries adopt technologies more suitable for skilled workers, as proposed in Caselli and Coleman (2006), or, more generally, because features such as the institutional setting or sectoral composition differentially affect the productivity of high- and low-skill labor. On the other hand, as proposed in Jones (2014a), the gap in embodied human capital between high- and low-skill workers might be larger in rich countries, because of differences in educational quality, training or workers' intrinsic characteristics (the "relative human capital" interpretation). This distinction led to substantial disagreement on the role of human capital in development accounting (Caselli and Ciccone, 2019; Jones, 2019). Depending on which interpretation is chosen, differences in the relative human capital of high-skill labor can explain from virtually none (under the "relative technology" interpretation) to all (under the "relative human capital" interpretation) of the the cross-country variation in economic performance.

In this paper I re-examine the measurement and intepretation of cross-country differences in relative skill efficiency. Using comparable micro-data for 12 countries at different levels of development, I show that gaps in the relative efficiency of high- and low-skill labor are sizable and, to a large extent, not driven by composition effects or other measurement issues. Building on this finding, I use data on foreign educated immigrants across several host countries to separately identify the role of the productive environment and embodied human capital in explaining the cross-country variation in relative skill efficiency.

The measurement contribution of the paper consists in the construction of comparable estimates for the two key inputs necessary for the calculation of relative skill efficiency: the skill premium and the relative supply of skilled labor. For the skill premium, previous work relies on imputations from meta-collections of estimated Mincerian returns, which tend to be scarcely comparable across countries and often at odds with the postulated human capital aggregator (which typically does not imply a log-linear relationship between wages and years of schooling). The relative supply of skilled labor is normally constructed from data on educational attainment in the working age population, therefore ignoring any cross-country variation in the employment rates and labor supply of high- and low-skill workers. I estimate the skill premium using the same specification and sample restrictions for all countries, and I compute the relative supply using actual information on employment status and hours worked.

Through the lens of a simple production function setting, I back out the relative efficiency of skilled labor for each country. I embed in this framework differences in both relative human capital and skill-bias of technology, and show that the estimated relative skill efficiency is a composite of the two. I confirm that relative skill efficiency is strongly increasing with GDP per worker. The measurement refinements I introduce have countervailing effects on the magnitude of these cross-country gaps: while the skill premium varies more across countries than what can be inferred from Mincerian returns (implying less dispersion in relative skill efficiency), accounting for the labor supply margin leads to larger gaps in the relative supply of skilled labor (implying more dispersion in relative skill efficiency). Moreover, I leverage the individual-level information available in my dataset to show that, to a large extent, cross-country gaps in relative skill efficiency are not driven by differences in sectoral composition, in the incidence of self-employment or in the returns to other observable characteristics, such as gender and experience.

I then study the interpretation of the cross-country variation in relative skill efficiency. My approach is based on the analysis of migrant workers, educated in their countries of origin but observed in the same labor market. I extend the baseline framework to allow for the fact that workers educated in different countries might have different human capital endowments, and differentially so depending on their level of educational attainment. Gaps in the relative human capital of skilled labor might reflect differences in educational quality, as emphasized in Schoellman (2012), or differential sorting into higher education across countries. In this setting, the variation in skill premia across countries of origin and host countries allows to discriminate between the "relative human capital" and "relative technology" interpretations of relative skill efficiency. Intuitively, foreign-educated migrants employed in the same host country are exposed to an equally skill-biased technological and institutional environment, and cross-nationality differences in the skill premium identify differences in the relative human capital endowment of high-skill labor. Moreover, for a given country of origin, differences in the skill premium across host countries are informative on differences in the skill bias of technology and the relative price of high-skill labor.

I find that the relative human capital of skilled labor accounts for a minor share - 5% to 18%, with a baseline estimate of 9% - of the cross-country variation in relative skill efficiency. This result is driven by the fact that cross-nationality differences in the wage gap between high- and low-skill immigrants in the same host country are much smaller than the corresponding cross-country differences in relative skill efficiency. I consider several threats to the validity of a strategy based on migrants for cross-country inference: differential selection into migration, skill loss upon migration and differential sorting into sectors or local labor markets. I show that accounting for these possibilities does not majorly affect the quantitative conclusions of the paper and, if anything, tends to lower the contribution of relative human capital. As a validation exercise, I also document that the estimated variation in relative human capital is roughly in line with what can be inferred, for a smaller set of countries, from differences in the relative performance of high- and low-educated adults in standardized tests.

I conclude the paper by discussing the implications for development accounting. I use the migrant-based estimates to implement a simple counterfactual exercise, where a poor country is assigned the quantity and relative human capital of high- and low-skill labor observed in a rich country. I emphasize two key results. First, the income gains for the poor country are limited, only marginally larger than what would be obtained by assuming no cross-country variation in relative human capital, as in Caselli and Ciccone (2019). This implies that large cross-country differences in average human capital require large *uniform* differences across skill levels (i.e. all workers, irrespectively of the skill level, having more human capital in rich countries), as opposed to *relative*, putting important restrictions on the possible sources of these gaps. Second, differently from Jones (2014a), the results are largely invariant to the value of the elasticity of substitution between high- and low-skill labor. Once the one-to-one link between relative skill efficiency and relative human capital is broken, imperfect substitutability does not amplify the role of human capital in development accounting.

My work fits within the literature on cross-country differences in the structure of production. The basic approach to isolate skill-biased differences in productivity is introduced by Caselli and Coleman (2006), and subsequently updated by Caselli (2016). Malmberg (2018) proposes an alternative methodology, based on trade data, to infer cross-country differences in the efficiency of skilled labor, and discusses the implications for development accounting. Compared to these papers, my main contributions are (i) a richer account of the cross-country gaps in relative skill efficiency, made possible by the use of cross-country micro-level data, and (ii) a migrant-based decomposition of relative human capital and technology as sources of these gaps.[1] The second exercise relates to Okoye (2016), which uses the Mincerian returns for US immigrants estimated in Schoellman (2012) to discipline the cross-country variation in relative human capital in the context of a model with imperfect substitutability between skill groups and skill-biased technology adoption. My work differs in terms of both empirical implementation and focus of the analysis. Methodologically, I add to Okoye (2016) by using skill premia estimated from micro data from multiple countries, by computing a decomposition of the cross-country variation in relative skill efficiency and by quantifying the effects of several possible confounders associated with a migrant-based identification strategy. Moreover, while Okoye (2016) focuses on the extent to which poor countries face barriers to the adoption of skill-specific technologies, I use my decomposition results to shed light the ongoing debate on the role of human capital and imperfect substitutability in development accounting.

This paper also belongs to a growing literature studying migrants' wages to learn about cross-country differences in average human capital (Schoellman, 2012, 2016; Lagakos et al., 2016; Hendricks and Schoellman, 2018, 2020). Compared to these papers, my work isolates the role of the *relative* human capital endowment of high- and low-skill workers, whose quantitative

[1]The distinction between the relative human capital and technology mirrors, on a cross-country dimension, a corresponding debate on the causes of the rise of the skill premium over time (Acemoglu, 1998, 2002; Bowlus and Robinson, 2012; Hendricks and Schoellman, 2014).

importance is the subject of an open debate (Caselli and Ciccone, 2019; Jones, 2019). As I discuss in Section V, my findings can be combined with the existing evidence on migrants' labor market outcomes to provide a more comprehensive understanding of the cross-country variation in human capital and technology.

The paper is structured as follows. Section I describes the data I use in this study. Section II introduces the basic framework and describes the measurement of relative skill efficiency. Section III discusses the migrant-based quantification, while Section IV discusses potential identification concerns and the robustness of the results. Section V illustrates the implications for development accounting, and Section VI concludes by discussing further implications and directions for future work.

I Data

The primary data source for the paper is a collection of nationally representative Census data harmonized by IPUMS and IPUMS International (Ruggles et al., 2019; Minnesota Population Center, 2019). I consider all countries with at least one cross-section of data in 1990-2010, and available information on wages or earnings, education, labor market status, gender, experience and sector of employment. This leaves 26 cross-sections from 12 countries, including (according to the World Bank classification) high-income (United States, Canada, Israel, Trinidad and Tobago), upper middle-income (Mexico, Panama, Uruguay, Venezuela, Brazil, Jamaica) and lower middle-income (Indonesia, India) countries. In what follows, I refer to these 12 countries as the "micro-data sample". For most of the analysis, I focus on the cross-sections from 2000 or the closest available year within each country (results for other cross-sections are reported in Appendix B).

For wage employed workers, I construct hourly wages from available information on annual or weekly wages and hours worked. The information on hours worked is not available for India and Panama; for these countries, I simply use weekly wages (as opposed to hourly) to estimate skill premia and counts of employed workers (as opposed to hours worked) to calculate labor stocks. Whenever the underlying Census includes the necessary information, I also construct a measure of hourly or weekly self-employment income, which I use for a robustness check. I classify all employed workers into five levels of educational attainment: primary or less, lower secondary, upper secondary, some tertiary and tertiary completed. I define (potential) experience as the difference between current age and age at the end of education, using data from the World Bank's World Development Indicators (World Bank, 2017) to infer the country-specific duration of each education stage. Additional details on the construction of the key variables can be found in Appendix A.

Within four of the countries in the micro-data sample (Brazil, Canada, Israel and United States), I observe foreign-born and foreign-educated individuals from a total of 102 countries of origin, satisfying a number of sample restrictions dicussed in Section III. I refer to these 102 countries - for which I am able to construct estimates of the relative human capital endowment of high-skill labor - as the “broad sample”. For all countries, I measure real GDP per worker in PPP terms from the Penn World Table (Feenstra et al., 2015).

II Measuring Relative Skill Efficiency

This section documents how the relative efficiency of skilled labor varies across countries. I start by introducing a general framework, which I use to illustrate the nature of the empirical exercise and to fix the terminology used in the rest of the paper. I then discuss the baseline exercise, followed by a number of extensions.

II.A Framework

Throughout the paper, I consider variants of the production technology

$$Y_c = A_c F(A_{K,c}K_c, A_{1,c}X_{1,c}, \ldots, A_{N,c}X_{N,c}) \tag{1}$$

where c indexes countries, K_c is physical capital and $X_{1c}, \ldots, X_{Nc}$ are different types of labor services. In the baseline exercise, different types of workers correspond to different levels of educational attainment; in a subsequent extension, I also differentiate them by gender and experience. The production function involves several technological paramenters, potentially varying across countries: A_c is total factor productivity, while $A_{K,c}, A_{1,c}, \ldots, A_{N,c}$ are factor-biased technological terms, augmenting physical capital and labor services.

The embodied productivity of workers is potentially different across labor types and across countries. In particular, the amount of labor services supplied by labor type n is

$$X_{n,c} = Q_{n,c}\tilde{X}_{n,c} \tag{2}$$

where $\tilde{X}_{N,c}$ represents the number of hours worked by workers of type n employed in country c, while $Q_{n,c}$ captures workers' embodied productivity, i.e. the hourly amount of labor services they provide. While $A_{1,c}, \ldots, A_{N,c}$ proxy for factors external to individuals, such as the available technologies and the features of the working environment, $Q_{1,c}, \ldots, Q_{N,c}$ capture workers' human capital, which is the result of both accumulated knowledge and innate characteristics.

Workers of type n in country c provide therefore $A_{n,c}Q_{n,c}$ efficiency units. Workers' efficiency is a function of their human capital and the particular technology they have access to. Consider two types of workers indexed by H and L. Under perfectly competitive labor markets, the wage ratio is

$$\frac{w_{H,c}}{w_{L,c}} = \frac{A_{H,c}Q_{H,c}}{A_{L,c}Q_{L,c}} \frac{F_H(A_{K,c}K_c, A_{1,c}X_{1,c}, \ldots, A_{N,c}X_{N,c})}{F_L(A_{K,c}K_c, A_{1,c}X_{1,c}, \ldots, A_{N,c}X_{N,c})} \tag{3}$$

i.e. the product of the relative efficiency of workers of type H and L ($\frac{A_{H,c}Q_{H,c}}{A_{L,c}Q_{L,c}}$) and the relative price of an efficiency unit supplied by the two types. Equation (3) is the relationship I bring to the data to measure the relative efficiency of high- and low-skill labor. In order to do that, I need to (i) identify high- and low-skill workers, (ii) measure the corresponding wage ratio and (iii) impose further structure to back out the relative price of high- and low-skill efficiency units. I start from a baseline set of assumptions in the next section, and discuss several alternatives in the following one.

II.B Baseline Specification

Setup. I follow Caselli and Coleman (2006) and most of the subsequent literature in considering a CES human capital aggregator of high- and low-skill labor, with physical capital and labor assumed to be separable. More specifically,

$$Y_c = A_c F\left[A_{K,c}K_c, G\left(A_{L,c}L_c, A_{H,c}H_c\right)\right] \tag{4}$$

where the human capital aggregator G is given by

$$G\left(A_{L,c}L_c, A_{H,c}H_c\right) = \left[\left(A_{H,c}H_c\right)^{\frac{\sigma-1}{\sigma}} + \left(A_{L,c}L_c\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{5}$$

Here, H_c and L_c denote high-skill and low-skill labor services, and σ is the elasticity of substitution between the two. High- and low-skill labor services are given by the product of the number of hours worked by each type and their human capital

$$H_c = Q_{H,c}\tilde{H}_c \tag{6}$$

$$L_c = Q_{L,c}\tilde{L}_c \tag{7}$$

The skill premium, i.e. the relative hourly wage of high- and low-skill workers, is

$$\frac{w_{H,c}}{w_{L,c}} = \left(\frac{A_{H,c}Q_{H,c}}{A_{L,c}Q_{L,c}}\right)^{\frac{\sigma-1}{\sigma}}\left(\frac{\tilde{H}_c}{\tilde{L}_c}\right)^{-\frac{1}{\sigma}} \tag{8}$$

I refer to $\frac{A_{H,c}Q_{H,c}}{A_{L,c}Q_{L,c}}$ as the relative efficiency of high- and low-skill workers (or, for brevity, relative skill efficiency). If $\sigma > 1$, the empirically relevant case given the existing estimates of the elasticity of substitution (Ciccone and Peri, 2005), a higher efficiency of skilled labor raises the skill premium, conditional on factor supplies. The relative efficiency can vary across countries because of differences in the skill bias of technology, $\frac{A_{H,c}}{A_{L,c}}$, and differences in the relative human capital of skilled labor, $\frac{Q_{H,c}}{Q_{L,c}}$. In what follows, I normalize the relative efficiency of skilled labor so that it is 1 for the United States.

Elasticity Notation. I summarize the cross-country variation of any quantity of interest X_c

with the corresponding elasticity with respect to GDP per worker $\theta_X \equiv \frac{\partial \log X_c}{\partial \log y_c}$. Moreover, for brevity I refer to the elasticities of relative skill efficiency as θ_{AQ}, of relative human capital as θ_Q, of the skill bias of technology as θ_A, and of the skill premium as θ_W. From (8), the elasticity of relative skill efficiency can be written as

$$\theta_{AQ} = \theta_A + \theta_Q = \frac{\sigma}{\sigma - 1}\theta_W + \frac{1}{\sigma - 1}\theta_{\tilde{H}/\tilde{L}} \tag{9}$$

Implementation. To bring this framework to the data, two key choices to be made are the assigment of workers to the high- and low-skill categories and the calibration of the elasticity σ. For my baseline, I consider high-skill all workers with some tertiary education, while individuals with at most upper secondary degrees are low-skill. This split is in the middle range of what the literature has considered. For the elasticity of substitution, I rely on Ciccone and Peri (2005), who provide a credibly identified estimate of $\sigma = 1.5$ on US data. I perform robustness checks on both choices in Section C and Appendix B.

Within each of the two skill categories, workers are perfect substitutes. They provide different quantities of efficiency units per hour depending on their educational attainment, as captured (given the perfect substitutability assumption) by their relative wages. The aggregators $\tilde{H}_c$ ($\tilde{L}_c$) are expressed in terms of equivalent hours supplied by tertiary (upper secondary) educated workers, which I refer to as "baseline" high-skill (low-skill) workers. They take the form

$$\tilde{H}_c = \sum_{n \in \mathcal{H}} \frac{w_{H,c,n}}{w_{H,c,\text{tertiary}}} \tilde{H}_{c,n} \tag{10}$$

$$\tilde{L}_c = \sum_{m \in \mathcal{L}} \frac{w_{L,c,m}}{w_{L,c,\text{upper secondary}}} \tilde{L}_{c,m} \tag{11}$$

where $w_{H,c,n}$, $w_{L,c,m}$, $\tilde{H}_{c,n}$ and $\tilde{L}_{c,m}$ denote the wages and total hours worked by high- and low-skill workers with education levels n and m, with $n \in \mathcal{H} = \{\text{some tertiary, tertiary}\}$ and $m \in \mathcal{L} = \{\text{primary, lower secondary, upper secondary}\}$.[2] For each country, I run a log-wage regression with the five educational categories as controls on a sample of wage-employed workers with a relatively high degree of labor market attachment (16 to 65 years-old, working at least 30 hours per week and, if this information is available, 30 weeks per year) and calculate all $w_{H,c,n}$'s and $w_{L,c,m}$'s as the exponentials of the corresponding estimates. The skill premium is then given by the wage ratio between baseline high- and low-skill workers. Finally, $\tilde{H}_{c,n}$ and $\tilde{L}_{c,m}$ are computed by summing up the hours worked by all workers (including the self-employed) in the relevant educational categories. With the country-specific estimates of $\frac{\tilde{H}_c}{\tilde{L}_c}$ and

[2] The within-skill-group differences in efficiency units can in principle be driven by a combination of embodied human capital and education-specific technology. Indeed, strictly speaking here I am backing out the relative efficiency of tertiary and upper secondary educated workers, but the magnitude of relative skill efficiency will in general depend on the chosen baseline types of high- and low-skill workers. Appendix B.5.4 defines and quantifies a measure of "average" relative skill efficiency, which combines the relative efficiency of all high- and low-skill workers. The cross-country variation in this measure is similar to the one shown here.

$\frac{w_{H,c}}{w_{L,c}}$ at hand, I can back out $\frac{A_{H,c}Q_{H,c}}{A_{L,c}Q_{L,c}}$ from (8).

Comparison with Traditional Measurement. At this point it is useful to remind the reader of the key differences with respect to the "traditional" measurement of relative skill efficiency without micro data, as typically implemented in the literature (Caselli and Coleman, 2006; Jones, 2014a). First, relative wages are typically imputed based on meta-collections of estimated Mincerian returns, or - given the lack of systematic cross-country variability in the estimates in such collections - simply assuming a common Mincerian return of 10%. This might be inaccurate for a number of reasons: (i) the estimates in these meta-collections are often scarcely comparable in terms of empirical specifications, sample size and composition; (ii) imputing wages based on Mincerian returns ignores non-linearities in the relationship between log wages and years of schooling, which are both natural in a setting with imperfect substitution between high- and low-skill workers and, according to the existing evidence, empirically important (see for example Lemieux, 2006). Second, the supply terms $\tilde{H}_{c,n}$ and $\tilde{L}_{c,m}$ are constructed from data on the educational attainment of the working age population, as opposed to hours worked by the employed. To the extent that there are cross-country differences in the relative labor supply of high- and low-skill individuals, either on the extensive or intensive margin, this might over- or under-estimate the cross-country variation in $\frac{\tilde{H}_c}{\tilde{L}_c}$.

Results. The first three columns of Table I display the skill premia, relative skill supplies and relative efficiencies for all countries in the micro-data sample. As summary statistics for the cross-country variation, the last row reports the elasticities θ_W, $\theta_{\tilde{H}/\tilde{L}}$ and θ_{AQ}.

[Table I here]

The skill premium is on average higher in poorer countries, but the range of its variation is relatively modest. Coupled with the large gaps in the relative supply displayed in the second column, this implies large cross-country differences in the relative efficiency of skilled labor (third column). The magnitudes are striking: in this sample, a given increase in GDP per worker is associated to a more than proportional increase in relative skill efficiency. The gap with respect to the US ranges from a factor of 1.4 for Canada to a factor of 100 or more for the poorest countries in the sample. Figure I displays graphically the strong and positive relationship between relative skill efficiency and GDP per worker.

[Figure I here]

The last three columns of Table I deconstruct the differences with the traditional approach for measuring relative skill efficiency. Columns 4 and 5 show the results when the relative supply of skilled labor is constructed by counting employed workers as opposed to hours (column 4), and by counting working age individuals as opposed to employed workers (column 5). Ignoring the intensive and, especially, the extensive margins of labor supply leads to an understatement of the cross-country dispersion in the relative supply of skilled labor, and, as a consequence, in the inferred relative skill efficiency. This is driven by systematic cross-country differences in the skill-specific labor supply, illustrated in Figure II: (i) while all employed workers tend to work fewer hours in rich countries compared to poor countries, this relationship is (mildly) weaker for high-skill workers; (ii) the employment rate is increasing with GDP per worker for the high-skill, and decreasing for the low-skill. The combination of (i) and (ii) implies that the relative labor supply of working age high- and low-skill individuals is higher in rich countries. This is consistent with the evidence reported in Bick et al. (2016) for a different set of countries.

[Figure II here]

The last column of Table I fully replicates the "traditional" approach for measuring relative skill efficiency on my data. These estimates are based on skill premia and labor stocks constructed assuming a common Mincerian return of 10% across all countries (and, as in column 5, using educational attainment in the whole working age population). The resulting cross-country variation in relative skill efficiency is now slightly higher compared to the baseline estimates in column 3. Assuming constant skill premia amplifies the differences in relative efficiency because the skill premium is, in fact, negatively correlated with GDP per worker and the relative supply of skilled labor. Appendix B.5.1 shows that country-specific estimates of Mincerian coefficients from various sources also understate this negative correlation, and that this is the case even when I use Mincerian returns estimated from the same IPUMS data used for the baseline estimates of the skill premium. A reason for this is that in most countries returns to schooling are in fact convex, and a higher prevalence of low-educated individuals in the sample (as it is the case for the poorer countries) mechanically lowers the estimated linear relationship between log wages and years of schooling.

Overall, these results imply that (i) the relative supply of skilled labor is more positively correlated with GDP than what is suggested by educational attainment data, implying larger cross-country gaps in relative skill efficiency for a given skill premium, and (ii) the skill premium is more negatively correlated with GDP than what suggested by Mincerian returns, implying smaller cross-country gaps in relative skill efficiency. Since (ii) slightly dominates on (i), the gaps in relative skill efficiency inferred with micro data are slightly smaller (though still large in absolute terms) than the ones resulting from the traditional sources.

II.C Robustness

This section exploits the richness of the micro-level information in the IPUMS data to verify the extent to which gaps in relative skill efficiency reflect compositional effects and other measurement issues. For each exercise, I present the results in terms of elasticities with respect to GDP per worker in Table II; country-specific results and more details on the implementation can be found in Appendix B.

[Table II here]

Experience and Gender. Row (2) of Table II shows the results when allowing for heterogeneity in terms of two additional observable characteristics: experience and gender. This is potentially important as the demographic composition of high- and low-skill labor differs across countries, and the wage returns to these observable characteristics have also been shown to vary substantially across educational groups and with the level of development (Lagakos et al., 2017). I compute skill premia and labor stocks under the assumption that workers within skill groups are perfect substitutes, with their efficiency allowed to depend on potential experience and gender (see Appendix B.1 for the details). Compared to the baseline estimates reported in row (1), both the relative wage and the relative supply vary slightly less across countries; the resulting relative skill efficiency is still substantially increasing with development, with a marginally higher elasticity with respect to GDP per worker.

Self-Employment. It is well-known that self-employment is more widespread in poor countries compared to rich countries. While the self-employed enter in the computations of the labor stocks, by construction they are not part of the specifications to estimate skill premia. This might be problematic to the extent that the efficiency gap between high- and low-skill individuals is different for self-employed and wage workers. To investigate this issue, I use data on self-employment income, which is available for 8 countries in the micro-data sample (Brazil, Canada, Israel, Mexico, Panama, Trinidad and Tobago, United States and Venezuela). Naturally, this includes in principle payments to both capital and labor. However, it is useful to have a sense of how much the conclusions of my exercise change if both wage and self-employed income are used in the regressions estimating skill premia. To the extent to which the highly-educated self-employed use more physical capital, these regressions might overestimate skill premia relatively more in poor countries (where the self-employed are more prevalent), therefore putting the odds against finding the result that relative skill efficiency is higher in rich countries. Row (4) of Table II shows that the impact of this correction is in fact minimal, and the elasticities are very similar to their baseline counterparts computed over the same eight countries, reported in row (3).

Relative Skill Efficiency across Sectors. I next turn to the role of sectorial heterogeneity. It is plausible that the production technology varies across sectors; at the same time, rich and poor countries differ dramatically in their sectoral composition of employment. An interesting question is therefore the extent to which the cross-country variation in "aggregate" relative skill efficiency is driven by sectoral composition, as opposed to within-sector differences.[3]

To shed light on this, I postulate a sector-level production function. Suppose the production

[3] The exercise in this section is closely related to a number of papers that study the role of sectoral composition in driving differences in the relative supply of skilled labor, either over time or across countries (Berman et al., 1994, 1998; Machin and Reenen, 1998; Hendricks, 2010). Here I ask a similar question for cross-country gaps in the inferred aggregate relative skill efficiency.

technology for sector s in country c is

$$Y_{c,s} = F_{c,s}\left(K_{c,s}, \left[(A_{H,c,s}H_{c,s})^{\frac{\tilde{\sigma}-1}{\tilde{\sigma}}} + (A_{L,c,s}L_{c,s})^{\frac{\tilde{\sigma}-1}{\tilde{\sigma}}}\right]^{\frac{\tilde{\sigma}}{\tilde{\sigma}-1}}\right) \tag{12}$$

where the sector-level elasticity of substitution is denoted by $\tilde{\sigma}$ (to distinguish it from the aggregate elasticity σ). The skill premium in sector s is given by

$$\frac{w_{H,c,s}}{w_{L,c,s}} = \left(\frac{A_{H,c,s}Q_{H,c,s}}{A_{L,c,s}Q_{L,c,s}}\right)^{\frac{\tilde{\sigma}-1}{\tilde{\sigma}}} \left(\frac{\tilde{H}_{c,s}}{\tilde{L}_{c,s}}\right)^{-\frac{1}{\tilde{\sigma}}} \tag{13}$$

As for the aggregate case, sector-specific relative skill efficiencies can be backed out using sector-specific skill premia and labor stocks, as well as a calibrated value for the elasticity of substitution.

I consider four broad sectors that can be consistently defined across all 12 countries in the micro-data sample: agriculture, industry, low-skill services and high-skill services. The mapping between the IPUMS sectoral classification and these broader sectors follows Herrendorf and Schoellman (2018). One complication arises from the fact that estimates of the aggregate elasticity of substitution, such as the one in Ciccone and Peri (2005), are not directly informative on the corresponding elasticity at the sector level. If sectors differ in skill intensity, any estimate of the aggregate elasticity will partially reflect the reallocation of resources across different sectors in response to a change in the skill premium. To calibrate $\tilde{\sigma}$, I apply the theoretical results in Oberfield and Raval (2014), that derives a general mapping between the aggregate and the micro-level elasticities of substitution among two factors of production. This computation (illustrated in Appendix B.2) implies $\tilde{\sigma} = 1.59$, in fact close to the aggregate elasticity.

Rows (5)-(8) of Table II show the sector-level results. Relative skill efficiency is strongly increasing in GDP per worker within all sectors. This suggests that differences in sectorial composition are not the main driver of the overall dispersion in relative skill efficiency. However, there are also cross-sector differences; the cross-country gap is largest in agriculture and smallest in high-skill services, which is mostly driven by a stronger gradient of relative skill supply in less skill-intensive sectors, such as agriculture.[4] In Appendix B.2 I build on these estimates to perform a simple counterfactual exercise that, imposing more structure on the demand side of the model, quantifies the residual variation in relative skill efficiency if sectorial employment shares were equalized across countries. The resulting θ_{AQ} is about 12% lower than the baseline in Table II. This confirms that, while sectoral composition plays some role, relative skill efficiency gaps are primarily a within-sector phenomenon.

[4]The country-specific results reported in Appendix B.6 show that within all countries relative skill efficiency is highest in high-skill services and lowest in agriculture, with manufacturing and low-skill services displaying intermediate values. However, as implied by the elasticities in Table II, these cross-sector differences are smaller in richer countries.

Elasticity of Substitution. I now illustrate how the results vary with the elasticity of substitution. The value of 1.5 is based on arguably the most credibly identified estimate in the literature, exploiting exogenous variation in the relative supply of high-skill labor across US States (Ciccone and Peri, 2005). This value is not far from alternative estimates based on US data: the seminal paper by Katz and Murphy (1992) finds $\sigma = 1.41$, while other estimates range between 1.3 and 2 (see the reviews in Autor et al., 1998; Ciccone and Peri, 2005).The last two columns of Table II show the results for the two extremes of this range. The magnitude of θ_{AQ} is quite sensitive to the value of σ, with more substitutability implying less dispersion in relative skill efficiency. However, even for $\sigma = 2$, cross-country differences are large, with the gap with respect to the US ranging from a factor of 1.3 (Canada) to a factor of 17 (Indonesia).[5]

It is useful to highlight here the relationship with the elasticity estimated in Hendricks and Schoellman (2020) and Bils et al. (2020). These papers show that models where the skill bias of technology responds endogenously to the relative supply of high-skill labor are isomorphic to a production function with no cross-country differences in the factor-biased technology terms and a "long-run" elasticity of substitution, σ^{LR}. The elasticity σ^{LR} is necessarily larger than σ, as it incorporates the postulated adjustment of $A_{H,c}/A_{L,c}$ to differences in labor supply (treated as exogenous); the larger the difference between σ^{LR} and σ, the more the endogenous skill bias of technology varies across countries.[6] I compute σ^{LR} as the σ that solves (9) when $\theta_A = 0$ (see Appendix B.3 for more details). Using the values of θ_W and $\theta_{\tilde{H}/\tilde{L}}$ reported in Table I and the baseline estimate of θ_Q presented in Section III, I find $\sigma^{LR} = 4.58$, roughly in line with Hendricks and Schoellman (2020) and Bils et al. (2020). Through the lens of models of directed technology adoption, the high value of σ^{LR} compared to conventional estimates of σ is a reformulation of the result of large cross-country gaps in relative skill efficiency.[7]

Different Production Technologies. Finally, I discuss how different specifications of the production technology explored in the literature affect the interpretation of relative skill efficiency. First, with capital-skill complementarity as in Krusell et al. (2000), the skill premium is increasing in the stock of equipment capital, and the relative skill efficiency computed from (8) incorporates a term reflecting this effect. Appendix B.4.1 includes a simple calibration exercise suggesting that this margin can be quantitatively important, accounting for about half of the cross-country dispersion in relative skill efficiency. This gives a particular underpinning of skill-biased differences in the productive environment: rich countries are relatively more abundant in the type of capital that is more complementary to high-skill labor.

[5]Appendix B.3 illustrates graphically the negative relationship between θ_{AQ} and σ implied by equation (9). The value of σ for which θ_{AQ} reaches 0 is 6.60.

[6]The estimates of σ discussed above might indeed not incorporate part or all of the endogenous adjustments of technology, either because they rely on short-run variation by controlling for trends (e.g., Katz and Murphy, 1992), or perhaps because they use within-country variation (e.g., Ciccone and Peri, 2005), while technology responses (especially the invention of new technologies) might affect the whole country.

[7]As I further discuss in the Conclusions, the quantitative importance of directed technological adoption vis-à-vis other mechanisms for cross-country differences in the skill bias of technology is an important open question for future work.

Second, with differentiated tasks and an endogenous division of labor as in Jones (2014b), cross-country differences in the organization of production might contribute to gaps in relative skill efficiency. Appendix B.4.2 illustrates that in a stylized version of this model, the relative skill efficiency computed from (8) depends on the degree of task specialization among high-skill workers, which in turn might vary across countries due to institutional factors, differences in factor supplies or multiple equilibria. While this is an intriguing possibility, in absence of further information on the performed tasks even worker-level data are not sufficient for a proper quantification of its importance.

Taking Stock. The results in this Section suggest that differences in relative skill efficiency are not an artifact of basic measurement or compositional issues.[8] Naturally, other relevant forces might operate at a more granular level than the one considered here, and further insights might come from the comparative analysis of finer micro-level data across countries. For example, comparable data on the task content of high-skill occupations might allow to quantify the role of the organization of production; moreover, firm-level data would allow to study the role of sorting of high- and low-skill into different kinds of firms, which might in principle contribute to the cross-country dispersion in "aggregate" relative skill efficiency. I leave these interesting extensions for future work.

III Interpreting Relative Skill Efficiency

What explains the variation in relative skill efficiency across countries? This Section exploits information on the skill premia of foreign-educated migrants to shed light on this question.

Setup. I modify the baseline framework in Section A by introducing a new dimension of heterogeneity: the fact that some workers are educated in different countries. For clarity, I abstract from educational careers spanning more than one country, and I consider only natives and migrants entirely educated in their own country of origin.

The human capital of high- and low-skill workers depends on the country where their education was acquired (indexed by a). This might reflect the quality of the educational environment, but also the mechanisms according to which individuals with different baseline characteristics sort into different levels of educational attainment. I do not take a stand on the source of embodied productivity differences between high- and low-skill labor, which might also be different across countries; I take as given their (possible) existence, and attempt to measure them in the data. Within skill groups, services provided by workers of different nationalities are perfect substitutes and augmented by the same technology. The production function takes the general

[8] Appendix B illustrates the implications of other robustness exercises, such as changing the definitions of high- and low-skill labor or considering different time periods. These exercises do not change the substance of the conclusion that relative skill efficiency is higher in rich countries.

from in equation (4), reported here for convenience

$$Y_c = A_c F\left[A_{K,c}K_c, G\left(A_{L,c}L_c, A_{H,c}H_c\right)\right] \tag{14}$$

with the total quantities of high- and low-skill services used for production in country c being

$$H_c = \sum_a Q_{H,a}\varepsilon^a_{H,c}\tilde{H}^a_c \tag{15}$$

$$L_c = \sum_a Q_{L,a}\varepsilon^a_{L,c}\tilde{L}^a_c \tag{16}$$

where $\tilde{H}^a_c$ and $\tilde{L}^a_c$ are the numbers of (baseline equivalent) hours worked by high- and low-skill workers educated in country a and employed in c. The terms $\varepsilon^a_{H,c}$ and $\varepsilon^a_{H,c}$ capture idiosyncratic factors affecting high- and low-skill immigrants from a in country c - including selection and skill loss upon migration - making their productivity in country c larger or smaller than $Q_{H,a}$ and $Q_{L,a}$; for natives, $\varepsilon^c_{H,c} = \varepsilon^c_{L,c} = 1$. For simplicity, I work under the assumption that foreign-educated immigrants represent a small share of the labor force, so that population-wide averages are well approximated by the corresponding averages among natives.

In a competitive labor market, the log wage ratio between high- and low-skill workers educated in country a and employed in country c is

$$\log\frac{w^a_{H,c}}{w^a_{L,c}} = \underbrace{\log\frac{A_{H,c}}{A_{L,c}}\frac{G_H\left(A_{L,c}L_c, A_{H,c}H_c\right)}{G_L\left(A_{L,c}L_c, A_{H,c}H_c\right)}}_{\text{Country } c \text{ FE}} + \underbrace{\log\frac{Q_{H,a}}{Q_{L,a}}}_{\text{Country } a \text{ FE}} + \underbrace{\log\frac{\varepsilon^a_{H,c}}{\varepsilon^a_{L,c}}}_{\text{Pair-Specific Term}} \tag{17}$$

This expression highlights why the country of education represents a useful source of variation for my purposes. All workers employed in country c face the same degree of technological skill bias and relative price of high- and low-skill efficiency units, the combination of which can be absorbed by a host country fixed effect. Moreover, human capital varies across countries of origin, and the relative human capital of high- and low-skill labor is captured by a country of origin fixed effect. Treating the pair-specific terms as random disturbances, one can quantify cross-country differences in relative human capital by comparing skill premia within a given host country. The key challenge is represented by the possibility that the pair-specific term might vary systematically across countries of origin, and, in particular, be correlated with their GDP per worker. I discuss several strategies to control for this possibility in what follows.

Implementation. To bring equation (17) to the data, I construct skill premia by country of origin for 4 host countries for which the IPUMS data records detailed information on immigrants: Brazil, Canada, Israel and the United States.[9] I implement the same sample restrictions as in

[9]These are the host countries in the IPUMS data for which all the following requirements are satisfied: (i) available information on country of birth, (ii) on year of immigration, and (iii) at least two foreign nationalities represented in the data, once all sample restrictions discussed below are applied. Some other countries in IPUMS satisfy some but not all these requirements.

Section II (16 to 65 years old wage-employed workers, working for at least 30 weeks and 30 hours per week in the previous year). To isolate the role of the country of education, I further restrict the sample to natives and immigrants who arrived at least six years after the age at which they should have ended their studies, given their level of educational attainment. For each host country, I pool all available cross-sections and run a log-wage regression on education-specific year and country of origin dummies; I then calculate $w_{H,c}^{a}$ and $w_{L,c}^{a}$ as the exponentiated estimates corresponding to tertiary and upper secondary educated workers. To account for basic factors affecting immigrants' productivity, I include as additional controls a cubic polynomial in the number of years since migration and, when available, self-reported proficiency in the local official language.[10]

I focus on 102 countries of origin with at least 50 upper secondary educated and 50 tertiary educated workers in the sample (the "broad" sample). Most of these countries of origin are represented in the US (101), while the other host countries have more limited coverage (11 in Canada, 8 in Brazil, 6 in Israel). While relative human capital (and its elasticity θ_Q) can be estimated for all 102 countries in the broad sample, the micro-data based estimates of relative skill efficiency (and its elasticity θ_{AQ}) only cover the 12 countries considered in Section II. To complement this, I also compute θ_{AQ} in the broad sample, using data on educational attainment from Barro and Lee (2013) and imputing wages based on a common Mincerian return of 10% (along the lines of the "traditional" approach described in Section IV).[11] For $\sigma = 1.5$, this gives $\theta_{AQ} = 1.107$ (s.e. 0.145), a bit lower than the estimate for the micro-data sample in Table I. As illustrated in Section II, this is not driven by measurement differences, which if anything tend to make micro-data based estimates slightly less different across countries, but rather by sample composition, as the rich countries in the micro-data sample have particularly high relative skill efficiency. In light of this, the discussion that follows focuses on the comparison of θ_Q and θ_{AQ} from the broader sample, though I also report results for the micro-data sample only.

Results - US Immigrants. I first present the results when focusing on the US as the only host country. This is a useful starting point, as the US is by far the host country with the largest diversity in immigrants' nationalities; moreover, these results serve as a baseline for the robustness analysis in Section IV, based on US data. From equation (17), the log difference between the skill premia of immigrants from country a and natives is given by

$$\log \frac{w_{H,US}^{a}}{w_{L,US}^{US}} - \log \frac{w_{H,US}}{w_{L,US}} = \log \frac{Q_{H,a}}{Q_{L,a}} + \log \frac{\varepsilon_{H,US}^{a}}{\varepsilon_{L,US}^{a}} \tag{18}$$

[10]Language proficiency is only available for US and Canada. In the US, respondents are asked to evaluate their English proficiency on a scale from 1 to 4. In Canada, respondents indicate whether the know either, neither or both English and French.

[11]The calculation of relative skill efficiency abstracts from the nationality composition of a country's labor force, which would in principle affect the effective relative skill supply if human capital endowments are indeed country-of-origin-specific. Once again, this is based on the fact that foreign-educated workers represent a minority of the labor force, and do not contribute much to country-wide averages of wages and human capital endowments. Moreover, this calculation excludes 10 countries not covered in the Barro and Lee (2013) data.

where $\frac{Q_{H,US}}{Q_{L,US}}$ is normalized to 1. This can be interpreted as a noisy estimate of relative human capital for country a. Under the assumption - assessed extensively in Section IV - that the difference between the US-specific productivity of high- and low-skill workers from a is uncorrelated with country a's GDP, a regression of (18) on $\log y_a$ recovers the elasticity of relative human capital θ_Q.

Figure III displays the skill premium as a function of GDP in the country of origin. While the correlation is positive, the range of variation is much smaller compared to the one of relative skill efficiency. Consider for example Switzerland and Vietnam, the 90^{th} and 10^{th} percentiles of the broad sample GDP distribution; the skill premium for Swiss-educated workers (1.81) is 1.22 times the skill premium for Vietnam-educated workers (1.48, a difference of 0.2 log points), while relative skill efficiency in Switzerland is 16 times larger than in Vietnam (a difference of 2.8 log points). Similar conclusions can be drawn for most pairwise comparisons between rich and poor countries in Figure III. Indeed, row (1) of Table III shows that the resulting θ_Q is 0.105, about 10% of the elasticity of relative skill efficiency θ_{AQ} in the broad sample for $\sigma = 1.5$. The Table also illustrates how the results vary with σ, which affects θ_{AQ} but not θ_Q; for the range of elasticities estimated in the micro literature, relative human capital accounts for a minority share of the variation in relative skill efficiency.

[Figure III and Table III here]

Results - All Host Countries. I then estimate (17) using all host countries, and regress the resulting country of origin fixed effects on GDP per worker to recover θ_Q. Row (2) of Table III shows that this gives $\theta_Q = 0.098$, accounting for about 9% of the elasticity of relative skill efficiency. The results are very similar to the US-based ones; indeed, in Appendix C, I illustrate that skill premia in all host countries are consistent with a θ_Q in that range or lower.

Having multiple host countries allows to additionally control for bilateral factors that might enter into $\log\left(\varepsilon^a_{H,c}/\varepsilon^a_{L,c}\right)$ in (17), and would be collinear to country of origin fixed effects in a single host country setting. I include sets of dummies identifying pairs of host and origin countries that are sharing a border or an official language, as well as a third degree polynomial in geographic distance between the two countries (all from the GeoDist dataset; see Mayer and Zignago, 2011). As shown in row (3), this results in a slightly lower estimate for θ_Q in the broad sample, not altering the key conclusion that relative human capital plays a minor role in the variation of relative skill efficiency.

Interpreting the Host Country FE. The left panel of Figure IV displays the estimated host country fixed effects from equation (17).[12] They are mildly decreasing in GDP per worker, with an elasticity of -0.17; keeping constant the relative human capital of high-skill labor, captured by the country of origin fixed effect, richer countries have lower skill premia. As

[12]The host country fixed effect is identified for all 12 countries in the micro-data sample, given that in all of them I observe at least one country of origin (including the country itself, for natives) observed in at least another country.

shown in equation (17), the host country fixed effect captures a combination of the skill bias of technology and the relative price of high-skill efficiency units. These two components can be separated with more structure on the production technology. The right panel of Figure IV shows that the skill bias of technology implied by the human capital aggregator in equation (5) with $\sigma = 1.5$ is strongly increasing in GDP per worker.[13] Intuitively, large cross-country differences in relative supply imply that the relative price of high-skill efficiency units should decline strongly with development, requiring large counteracting differences in the skill bias of technology to rationalize the (less variable) host country fixed effects.

[Figure IV here]

Different Production Technologies. Appendix C.3 illustrates how alternative formulations of the production technology change the interpretation of the host country fixed effect, while broadly preserving the interpretation of the country of origin fixed effects. Under capital-skill complementarity (Krusell et al., 2000), the host country fixed effects absorb differences in the abundance of equipment capital, which increases the skill premium for all workers employed in a given country; the country of origin fixed effects still capture relative human capital. In a model with sorting of high-skill labor into differentiated tasks (Jones, 2014b), the host country fixed effects absorb differences in the degree of task specialization, which affects the productivity of all high-skill workers; the country of origin fixed effects capture the relative human capital embodied in high-and low-skill workers, keeping the extent of the division of labor constant. An issue highlighted in such model is the extent of the skill transferability for immigrants from countries with a different organization of production; any loss of productive skills would be reflected in the pair-specific term in (17). The implications of this possibility are discussed in Section B.

IV Robustness and Extensions

The migrant-based estimates suggest small cross-country differences in the relative human capital of high- and low-skill labor. This section subjects this conclusion to several robustness checks. First, I exploit additional data on US immigrants to assess three potential concerns for the migrant-based approach: selection into migration, low skill transferability and differential sorting into sectors or local labor markets.[14] Second, I cross-validate the gaps in relative human capital estimated out of migrants with those implied by a different source, i.e. adults' performance in standardized tests.

[13]The host country fixed effect for country c is $\frac{\sigma}{\sigma-1}\log\left(A_{H,c}/A_{L,c}\right) - \frac{1}{\sigma}\log\left(Q_{H,c}/Q_{L,c}\right) - \frac{1}{\sigma}\log\left(\tilde{H}_c/\tilde{L}_c\right)$, which can be solved for $\log\left(A_{H,c}/A_{L,c}\right)$. Naturally, given an estimate of relative human capital, the skill bias of technology can also be computed as a residual from (8), using information on natives only. In Appendix C.2 I show that the resulting values are very similar to those computed from the host country fixed effects.

[14]These exercises focus on US-based immigrants because for the other host countries some or all of the additional data I use are unavailable.

IV.A Selection

It is helpful to explicitly introduce individual-level heterogeneity to the framework of Section III to illustrate the selection issue. Suppose that the human capital of individual i, of skill $S \in \{H, L\}$, having completed his or her education in country a is $Q_{S,a}\varepsilon_{S,a,i}$, where $\varepsilon_{S,a,i}$ is an idiosyncratic factor capturing unobservable skills, with $\mathbb{E}\left[\log \varepsilon_{S,a,i}\right] = 0$. Let $m^a_{c,i}$ be an indicator taking value 1 when individual i is a migrant from a to c. If migrants to country c are selected on unobservable skills, $\mathbb{E}\left[\log \varepsilon_{S,a,i} | m^a_{c,i} = 1\right] \neq 0$. In absence of other sources of country-of-origin-specific productivity, the skill premium gap between immigrants from a and US natives would then read

$$\log \frac{w^a_{H,US}}{w^{US}_{L,US}} - \log \frac{w_{H,US}}{w_{L,US}} = \log \frac{Q_{H,a}}{Q_{L,a}} + \underbrace{\mathbb{E}\left[\log \varepsilon_{H,a,i} | m^a_{US,i} = 1\right] - \mathbb{E}\left[\log \varepsilon_{L,a,i} | m^a_{US,i} = 1\right]}_{\text{Differential Selection}} \tag{19}$$

which is a particular specification of equation (18). Selection enters into the error term in (18) as long as it is differential across skill groups, i.e. $\mathbb{E}\left[\varepsilon_{H,a,i} | m^a_{US,i} = 1\right] \neq \mathbb{E}\left[\varepsilon_{L,a,i} | m^a_{US,i} = 1\right]$. Moreover, for the purpose of estimating θ_Q, differential selection is problematic if it is correlated with GDP per worker in the country of origin. In particular, a negative correlation - i.e. high-skill migrants from poor countries being more positively selected than low-skill migrants, relative to the same comparison for rich countries - could in principle countribute to the low θ_Q estimated in Section III.

The migration literature has widely established that migrants are non-randomly selected on observable and unobservable skills (Borjas, 1987), and for the vast majority of origin countries the degree of selection of emigrants to the United States appears to be positive (Feliciano, 2005). The issue of relative selection by educational achievement, i.e. how, among individuals educated in a given country, the degree of selection on unobservables of emigrants within the low-skill group compares to the one within the high-skill group, has received far less attention. Recent evidence comes from Hendricks and Schoellman (2018), who construct measures of selection on observable and unobservable skills based on the comparison of pre-migration wages of migrants to the US and wages of non migrants from the same country. Among other results, they report measures of selection by education, across bins of countries grouped by GDP per worker. In my notation, their measures of selection on unobservables for college and high-school educated migrants correspond to

$$Selection_{H,a} = e^{\mathbb{E}\left[\log \varepsilon_{H,a,i} | m^a_{US,i} = 1\right]} \tag{20}$$

$$Selection_{L,a} = e^{\mathbb{E}\left[\log \varepsilon_{L,a,i} | m^a_{US,i} = 1\right]} \tag{21}$$

so that by taking

$$\log \left(\frac{Selection_{H,a}}{Selection_{L,a}} \right) = \mathbb{E}\left[\log \varepsilon_{H,a,i} | m^a_{US,i} = 1\right] - \mathbb{E}\left[\log \varepsilon_{L,a,i} | m^a_{US,i} = 1\right] \tag{22}$$

I obtain the country-specific factor I need to correct for the selection bias in (19). Figure V displays this measure of differential selection across the GDP levels reported in Hendricks and Schoellman (2018). There does not appear to be any strong systematic pattern with respect to the level of development; if anything, the richest countries display the highest degree of positive differential selection, which would bias my approach towards finding a large θ_Q. Moreover, across all GDP levels, the selection correction is an order of magnitude smaller compared to the gaps in relative skill efficiency.

[Figure V here]

Row (4) of Table III shows the estimated θ_Q after the selection correction (where each country is assigned the degree of differential selection corresponding to its GDP group).[15] The relative human capital endowment of skilled labor contributes now only 2-7% to the association between relative skill efficiency and GDP per worker in the broad sample. This selection correction is quite crude, and might miss some heterogeneity in differential selection within GDP groups. However, these results do suggest that a reasonable degree of differential selection does not change the conclusion that relative human capital accounts for a limited part of gaps in relative skill efficiency.

IV.B Skill Loss and Skill Downgrading

Another concern is that skills might be partially country-specific. Differences in language, culture and the organization of production, as well as a poor fit between the educational curriculum and the needs of local employers could all imply a loss of productive skills upon migration. To the extent that this takes place differentially across skill levels, this will be reflected in the error term in equation (18), and might bias the estimate of θ_Q if it correlates with GDP per worker in the country of origin.

To assess the importance of this, I re-compute (18) limiting the sample to US migrants that are, according to obervable characteristics, less likely to be affected by a lack of US-specific human capital. Row (5) and (6) of Table III display the estimated θ_Q based on, respectively, migrants that have spent at least 10 years in the United States and migrants that report to speak English well. In both cases, the cross-nationality variation in skill premia and, as a consequence, in the inferred relative human capital of high-skill labor is somewhat smaller compared to the baseline case. This is consistent with the fact that poorer countries tend to be linguistically, institutionally and culturally more distant from the United States, making it harder for immigrants from those countries to fully utilize their skills.[16]

[15] I do not apply any selection correction to the estimate of relative human capital endowment for the United States, since when limiting the analysis to US-based workers this is identified out of natives.

[16] Schoellman (2012) implements a similar exercise for Mincerian returns, and similarly finds that limiting the sample to immigrants more and less abundant in US-specific human capital has a small impact on the dispersion of the estimated returns across countries of origin.

A more subtle issue is that some high-skill immigrants might effectively be employed as low-skill workers, and therefore be exposed to the low-skill augmenting technology and factor-specific price. This could reflect either barriers immigrants face when accessing high-skill jobs or, as emphasized in Jones (2014b), an optimal occupational choice given low skill transferability. For my purposes, this pattern can be problematic, since when comparing skill premia across nationalities as in (18) the technological and price terms would not fully cancel out.

To explore this issue, I rely on a proxy for the skill content of workers' activities based on their occupational title. In particular, I define an occupation as high- or low-skill based on the most frequent skill level among US natives in that occupation, and identify workers subject to "skill downgrading" as the high-skill employed in a low-skill occupation.[17] Figure VI shows that the incidence of skill downgrading does vary somewhat across countries of origin: on average, about 37% immigrants from countries in the lowest quartile of the GDP distribution are subject to it, while the corresponding figure across US natives is 17%.

[Figure VI here]

As a rough check on the implications of this for my results, I re-compute (18) excluding all skill-downgraded workers (either natives or immigrants) from the sample. Row (7) of Table III shows that this results in a slightly lower estimate of θ_Q.[18] Of course, this exercise is plausibly affected by a selection bias as, conditionally on educational attainment, immigrants employed in high-skill occupations are likely to differ in terms of unobservable characteristics from those employed in low-skill occupations. However, the small difference between the estimates on the restricted and baseline samples and the fact that, for most countries of origin, the skill-downgraded represent a minority of high-skill workers, suggest that it is unlikely that accounting for this type of selection would substantially increase the cross-country variation in relative human capital.

IV.C Sorting

The comparison of skill premia across nationalities identifies relative human capital gaps if migrants use the same technology and face the same relative price of high- and low-skill efficiency units. This might not be the case if, within a given host country, workers educated in different countries sort into labor markets that systematically differ along these dimensions.

I study two sources of within-country heterogeneity: sectors and regions. Consider first an

[17]This exercise uses *occ1990*, an occupation coding scheme harmonized across Census years by IPUMS, including almost 400 occupations. I repeat the skill intensity calculation separately for each year, and use the year-specific results to classify workers as skill-downgraded.

[18]This classification of high- and low-skill occupation implies that several (education-wise) low-skill workers are employed in high-skill occupations. When I estimate skill premia removing these workers from the sample as well, the resulting θ_Q is 0.093.

environment with a sector-specific production technology,

$$Y_{c,s} = A_{c,s}F\left(A_{K,c,s}K_{c,s}, A_{L,c,s}L_{c,s}, A_{H,c,s}H_{c,s}\right) \tag{23}$$

where $H_{c,s}$ and $L_{c,s}$ are sector-specific aggregates of high- and low-skill labor services. The wage ratio between high- and low-skill workers educated in country a and employed in sectors r and s is

$$\log \frac{w^a_{H,c,r}}{w^a_{L,c,s}} = \underbrace{\log \frac{p_{c,r}A_{c,r}}{p_{c,s}A_{c,s}}}_{\text{Sector}} + \underbrace{\log \frac{A_{H,c,r}}{A_{L,c,s}}\frac{F_{H,c,r}}{F_{L,c,s}}}_{\text{Sector} \times \text{Skill}} + \log \frac{Q_{H,a}}{Q_{L,a}} + \log \frac{\varepsilon^a_{H,c}}{\varepsilon^a_{L,c}} \tag{24}$$

Equation (24) illustrates how differential sorting can bias my empirical approach. On one hand, skill premia vary across nationalities if high-skill and low-skill workers differentially sort into sectors with different levels of revenue total factor productivity. This implies a sector-specific component in wages, which can be identified by a sector fixed effect in a log-wage regression. On the other hand, migrants could be differentially sorting into sectors with different skill bias of technology or relative prices of high- and low-skill efficiency units, which would imply sector-specific skill premia.

To evaluate the importance of these possibilities, I estimate the nationality-specific skill premia controlling for sector and sector $\times$ skill fixed effects, which absorb the sector-level terms highlighted in equation (24), and regress them on log GDP to recover θ_Q.[19] Row (8) of Table III shows the results. Allowing for sectoral heterogeneity has a small negative effect on the cross-country variation of relative human capital. While, as discussed in Section C, sectors are heterogeneous in terms of technology and skill prices, the allocation of migrants across sectors does not appear to be strongly related to these factors.

The last row of Table III reports the results of the corresponding exercise by region. I estimate skill premia net of skill-specific commuting zones fixed effects, constructed as in Autor and Dorn (2013). Commuting zones are commonly regarded as separate local labor markets, and as such should be well-suited to capture the spatial variation in the relative price of high- and low-skill efficiency units. The impact of this adjustment on the estimated θ_Q is once again small and negative.

IV.D Validation with Test Scores Data

This section investigates if measures of relative human capital based on international standardized tests are consistent with the conclusions of the migrant-based approach. I use data from the OECD's PIAAC programme (OECD, 2016), which includes nationally representative surveys

[19]I make full use of the sectoral classification available in the US Census and harmonized across years by IPUMS (*ind1990*), consisting of 243 different sectors.

of adult skills for 34 countries, collected in the 2011-2017 period.[20] I focus on the numeracy domain, and standardize scores to have an average of 0 and an individual-level standard deviation of 1 when pooling all countries (see Appendix A for more details on the data construction).

Figure VII plots the difference between the average score attained by college and high school educated workers against GDP per worker in 2014. High-skill individuals perform relatively better in richer countries, though differences in relative performance amount to fractions of an individual-level standard deviation (the slope of the relationship is 0.136). To evaluate the implications for relative human capital, I follow the development accounting literature in postulating a log-linear mapping between human capital and test scores, $\log Q_{S,c} = \beta T_{S,c}$, where $T_{S,c}$ is the average test score for skill group $S \in \{L, H\}$ in country c. The parameter β is pinned down by the wage increase associated to a standard deviation increase in test scores; a wage regression in the pooled sample (conditional on country fixed effects) gives $\widehat{\beta} = 0.203$, consistently with Hanushek et al. (2015). The implied elasticity of relative human capital is then $\theta_Q = 0.203 \times 0.136 = 0.028$, somewhat smaller than the migrant-based estimates in Table III.

[Figure VII here]

Naturally, test scores might fail to capture relevant dimensions of human capital, possibly differentially so across skill levels. Moreover, the PIAAC sample does not include very poor countries. The migrants-based estimates in Section III are preferable on both these accounts. On the other hand, this exercise is not subject to the migrant-related concerns discussed above. Overall, it is encouraging that these two different strategies point to a similar conclusion: the relative human capital of high-skill labor increases only mildly with development.

V Implications for Development Accounting

This section illustrates the implications of my results for the ongoing debate on the role of human capital in development accounting. Following Klenow and Rodríguez-Clare (1997), I write the production function in per worker terms as

$$y_c = Z_c \left[\left(A_{L,c} Q_{L,c} \tilde{L}_c \right)^{\frac{\sigma-1}{\sigma}} + \left(A_{H,c} Q_{H,c} \tilde{H}_c \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{25}$$

where Z_c captures TFP and capital intensity, and the size of the labor force is normalised to 1. Consider a poor (P) and a rich (R) country. A question of interest in development accounting

[20] Kaarsen (2014) and Bils et al. (2020) consider related exercises, exploiting the variation in standardized test performance across students attending consecutive grades. Focusing on test scores of adults with different levels of educational attainment allows me to avoid any assumption on the relationship between performance and years of schooling (which might be non linear), as well as to account for patterns of selection into higher education (which could in principle contribute to the cross-country variation in $Q_{H,c}/Q_{L,c}$).

is: how much would the poor country's income grow if it was assigned the human capital of the rich country?[21] Define the corresponding counterfactual GDP for the poor country as y_P^*, where

$$y_P^* = Z_P \left[\left(A_{L,P} Q_{L,R} \tilde{L}_R \right)^{\frac{\sigma-1}{\sigma}} + \left(A_{H,P} Q_{H,R} \tilde{H}_R \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{26}$$

Using the expressions for the equilibrium skill premia, the counterfactual GDP ratio between P and R can be written as

$$\frac{y_P^*}{y_R} = \frac{Q_{L,R}\tilde{L}_R}{Q_{L,P}\tilde{L}_P} \left[\frac{1 + \frac{w_{H,P}H_P}{w_{L,P}L_P} \left(\frac{y_R}{y_P}\right)^{\frac{\sigma-1}{\sigma}\theta_Q} \left(\frac{\tilde{H}_R/\tilde{L}_R}{\tilde{H}_P/\tilde{L}_P}\right)^{\frac{\sigma-1}{\sigma}}}{1 + \frac{w_{H,P}H_P}{w_{L,P}L_P}} \right]^{\frac{\sigma}{\sigma-1}} \Bigg/ \frac{y_R}{y_P} \tag{27}$$

where, for ease of reference to the results in Section III, I write relative human capital in terms of the elasticity $\theta_Q = \log\left(\frac{Q_{H,R}/Q_{L,R}}{Q_{H,P}/Q_{L,P}}\right) / \log\left(y_R/y_P\right)$.[22] The counterfactual GDP ratio is large when there are large differences in the relative human capital endowment of high-skill labor, as captured by θ_Q. Moreover, the ratio also increases with uniform gaps in human capital across skill levels, as captured, for a given θ_Q, by the $Q_{L,R}/Q_{L,P}$ term.

In absence of an estimate for θ_Q, previous work has relied on two opposite assumptions. Jones (2014a) assumes that all the variation in relative skill efficiency is due to human capital, that is $\theta_Q = \theta_{AQ}$. Caselli and Coleman (2006) and Caselli and Ciccone (2019) on the other hand interpret relative skill efficiency as reflecting only the skill bias of technology, with $\theta_Q = 0$. These diverging assumptions led to substantial disagreement on the role of relative human capital and imperfect substitutability in development accounting.

To illustrate the implications of my estimates of θ_Q for these debates, I compute (27) using the micro data from India (P) and US (R), the poorest and richest countries in the micro data sample. India's GDP per worker is 5.7% of the US one, and the estimates for relative human capital and relative skill efficiency imply the elasticities of $\theta_Q = 0.055$ and $\theta_{AQ} = 1.119$, roughly in line with the sample-wide values in Table III. As in the baseline exercises in Jones (2014a) and Caselli and Ciccone (2019), I set $Q_{L,R}/Q_{L,P} = 1$, which allows to isolate the contribution of relative human capital. Table IV displays the results.

[Table IV here]

Implication 1: Small Contribution of Relative Human Capital. Consider first the results for $\sigma = 1.5$. If, as in Jones (2014a), all the variation in relative skill efficiency is attributed

[21] As discussed in Jones (2019) and Hendricks and Schoellman (2020), a different thought experiment would be to assign to the rich country the human capital of the poor country, which is not simply the symmetric counterpart of the one considered here. Moreover, the magnitude of the contribution of human capital is sensitive to the chosen threshold for high-skill labor. See Hendricks and Schoellman (2020) for a full comparison of these variants of the development accounting exercise. Appendix D shows that Implications 1 and 2 discussed below largely apply to these alternative formulations.

[22] Appendix D includes a step by step derivation of equation (27). A similar representation is derived in Hendricks and Schoellman (2020).

to human capital ($\theta_Q = \theta_{AQ}$), closing the human capital gap would result in an increase in India's GDP of a factor of 12, up to 70% of the US level (roughly as Japan). On the other hand, if $\theta_Q = 0$ as in Caselli and Ciccone (2019), the same experiment would result in less of a doubling of India's GDP. My estimates imply that only 5% of the relative efficiency gap between US and India is driven by human capital; this implies a counterfactual ratio only slightly higher than the one with $\theta_Q = 0$, bringing India to 11% of the US GDP (roughly as Ukraine). While not negligible, the associated gain is small compared to the existing gap, with relative human capital contributing little to it. As shown in Figure VIII, similar conclusions apply to all the poorest countries in the micro-data sample, as well as to the (poorer) countries at the bottom of the GDP distribution in the broad sample.

[Figure VIII here]

It is useful to frame this result in the context of other papers performing development accounting with migration data. In particular, Hendricks and Schoellman (2018) show that wage gains upon migration are consistent with large gaps in average human capital per worker between the US and a combination of poorer countries. This variation in average human capital can be thought of as a composite of uniform and relative differences in human capital across skill levels. The results above suggest that, on their own, relative differences play a limited role, in line with the "relative technology" interpretation of the large gaps in relative skill efficiency. This does not preclude substantial cross-country gaps in human capital, which however require large uniform differences across skill levels. In their more recent work, Hendricks and Schoellman (2020) show that the relative wage gains of high- and low-skill migrants are consistent with significant human capital gaps for both skill groups and a predominant role of technology in explaining their relative productivity, consistently with my findings.[23]

Implication 2: No Amplification from Imperfect Substitutability. Another source of disagreement in the literature is the impact of σ on the development accounting results. Table IV shows that when $\theta_Q = \theta_{AQ}$ departures from perfect substitutability (i.e. a lower σ) greatly magnify the role of human capital. Intuitively, a lower σ leads to a higher estimated gap in relative skill efficiency, which is then fully attributed to human capital. On the other hand, Caselli and Ciccone (2013) show analytically that assuming imperfect substitutability reduces the contribution of human capital when $\theta_Q = 0$, as reflected by row (2) of Table IV. In Appendix D I show that this result extends to any (fixed) value of θ_Q; for a given estimate of relative human capital, lower values of σ are associated with lower counterfactual ratios. Row (3) of Table IV confirms this for my estimate of θ_Q.

[23] In previous work, Schoellman (2012) infers a significant variation in the relative human capital associated with schooling from the Mincerian returns for home-educated immigrants in the US. This conclusion is based on the calibration of a model of endogenous schooling, through the lens of which the cross-country variation in schooling quantity is informative on the cross-country variation in the productivity gain associated to an additional year of schooling (as in equilibrium the former increases the latter). The human capital stocks estimated by Schoellman (2012) incorporate this variation in relative productivity, which, as discussed in the paper, might in fact reflect both educational quality and the skill bias of technology.

In other words, the diverging patterns in Jones (2014a) and Caselli and Ciccone (2019) are due to conceptually different forces: the impact of σ on the measurement of θ_Q on one hand, and on the counterfactual ratio for a given θ_Q on the other. The migrant-based estimate of θ_Q is independent of σ, eliminating the first effect. To further illustrate the interplay between these two forces, row (4) in Table IV sets the θ_Q/θ_{AQ} ratio implied by the migrant-based calibration, allowing both θ_Q and θ_{AQ} to vary with σ (but keeping their ratio constant). The resulting counterfactual ratio increases more slowly with σ compared to row (3), due to a (weak) negative and counteracting effect of σ on the inferred θ_Q. Overall, both variants of the migrant-based calibration in Table IV show that σ does not have a major impact on the development accounting results, with departures from perfect substitutability mildly reducing the role of human capital.

VI Conclusions

This paper studies how the relative efficiency of high- and low-skill labor varies across countries. The analysis of micro data for 12 countries at different levels of development shows that highly educated workers are relatively more efficient in rich countries. This conclusion is not driven by differences in sectoral composition, incidence of self-employment or returns to other observable characteristics. The cross-nationality variation in the skill premia of foreign-educated migrants suggests that differences in the relative human capital endowment of high- and low-skill workers can account for a small share of these gaps. To a large extent, it is the productive environment (as opposed to embodied human capital) that makes high-skill labor relatively more efficient in rich countries.

These accounting results naturally call for a better understanding of the determinants of the skill bias of of the production technology. The existing literature, building on the theory in Caselli and Coleman (2006), mostly emphasizes skill availability at the country level as a factor driving skill-biased technological adoption. In addition, cross-country differences in various types of institutions, in the way production is organized and tasks are allocated across workers, and in the prevalence of large and modern corporations might all benefit disproportionately high-skill workers in rich countries, possibly also contributing to explaining their abundance. Along the lines of this paper, one likely source of further progress in the quantitative exploration of these possibilities is the comparative analysis of micro-level data on firms, tasks and workers.

Moreover, the results of this paper are informative for future work on human capital differences across countries. The small contribution of *relative* human capital in accounting for gaps in relative skill efficiency and income per worker does not imply that human capital plays a small role for economic development. What this result does suggest is that large cross-country gaps in human capital require large *uniform* differences across high- and low-educated workers. This puts important restrictions on theories of human capital accumulation and economic development, calling for a stronger emphasis on investments happening early on or outside of the formal school system. Identifying and quantifying these forms of human capital accumulation represent exciting avenues for future research.

References

Acemoglu, Daron, "Why Do New Technologies Complement Skills? Directed Technical Change And Wage Inequality," *The Quarterly Journal of Economics*, November 1998, *113* (4), 1055–1089.

— , "Directed Technical Change," *Review of Economic Studies*, October 2002, *69* (4), 781–809.

Autor, David H. and David Dorn, "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market," *American Economic Review*, 2013, *103* (5), 1553–97.

— , Lawrence F. Katz, and Alan B. Krueger, "Computing Inequality: Have Computers Changed the Labor Market?," *The Quarterly Journal of Economics*, 1998, *113* (4), 1169–1213.

Barro, Robert J. and Jong Wha Lee, "A New Data Set of Educational Attainment in the World, 1950-2010," *Journal of Development Economics*, 2013, *104* (C), 184–198.

Berman, Eli, John Bound, and Stephen Machin, "Implications of Skill-Biased Technological Change: International Evidence," *The Quarterly Journal of Economics*, 1998, *113* (4), 1245–1279.

— , — , and Zvi Griliches, "Changes in the Demand for Skilled Labor within U.S. Manufacturing: Evidence from the Annual Survey of Manufacturers," *The Quarterly Journal of Economics*, 1994, *109* (2), 367–397.

Bick, Alexander, Nicola Fuchs-Schündeln, and David Lagakos, "How do Average Hours Worked Vary with Development? Cross-Country Evidence and Implications," CEPR Discussion Papers 11092, C.E.P.R. Discussion Papers February 2016.

Bils, Mark, Baris Kaymak, and Kai-Jie Wu, "Labor Substitutability among Schooling Groups," Working Paper 2020.

Borjas, George J., "Self-Selection and the Earnings of Immigrants," *The American Economic Review*, 1987, *77* (4), 531–553.

Bowlus, Audra J. and Chris Robinson, "Human Capital Prices, Productivity, and Growth," *American Economic Review*, December 2012, *102* (7), 3483–3515.

Caselli, Francesco, *Technology Differences over Space and Time*, Princeton University Press, 2016.

— **and Antonio Ciccone**, "The contribution of schooling in development accounting: Results from a nonparametric upper bound," *Journal of Development Economics*, 2013, *104* (C), 199–211.

— **and** — , "The Human Capital Stock: A Generalized Approach: Comment," *American Economic Review*, March 2019, *109* (3), 1155–1174.

— **and Wilbur John Coleman**, "The World Technology Frontier," *American Economic Review*, June 2006, *96* (3), 499–522.

Ciccone, Antonio and Giovanni Peri, "Long-Run Substitutability Between More and Less Educated Workers: Evidence from U.S. States, 1950-1990," *The Review of Economics and Statistics*, November 2005, *87* (4), 652–663.

Feenstra, Robert C., Robert Inklaar, and Marcel P. Timmer, "The Next Generation of the Penn World Table," *American Economic Review*, 2015, *105* (10), 3150–3182.

Feliciano, Cynthia, "Educational selectivity in U.S. Immigration: How do immigrants compare to those left behind?," *Demography*, 2005, *42* (1), 131–152.

Hall, Robert E. and Charles I. Jones, "Why Do Some Countries Produce So Much More Output per Worker than Others?," *The Quarterly Journal of Economics*, February 1999, *114* (1), 83–116.

Hanushek, Eric A., Guido Schwerdt, Simon Wiederhold, and Ludger Woessmann, "Returns to skills around the world: Evidence from PIAAC," *European Economic Review*, 2015, *73* (C), 103–130.

Hendricks, Lutz, "Cross-country variation in educational attainment: structural change or within-industry skill upgrading?," *Journal of Economic Growth*, Sep 2010, *15* (3), 205–233.

— **and Todd Schoellman**, "Student abilities during the expansion of US education," *Journal of Monetary Economics*, 2014, *63* (C), 19–36.

— **and** — , "Human Capital and Development Accounting: New Evidence from Wage Gains at Migration," *The Quarterly Journal of Economics*, 2018, *133* (2), 665–700.

— **and** — , "Skilled Labor Productivity and Cross-country Income Differences," Working Paper May 2020.

Herrendorf, Berthold and Todd Schoellman, "Wages, Human Capital, and Barriers to Structural Transformation," *American Economic Journal: Macroeconomics*, April 2018, *10* (2), 1–23.

Jones, Benjamin F., "The Human Capital Stock: A Generalized Approach," *American Economic Review*, November 2014, *104* (11), 3752–3777.

_ , "The Knowledge Trap: Human Capital and Development Reconsidered," Working Paper 2014.

_ , "The Human Capital Stock: A Generalized Approach: Reply," *American Economic Review*, March 2019, *109* (3), 1175–1195.

Kaarsen, Nicolai, "Cross-country differences in the quality of schooling," *Journal of Development Economics*, 2014, *107* (C), 215–224.

Katz, Lawrence F. and Kevin M. Murphy, "Changes in Relative Wages, 1963–1987: Supply and Demand Factors," *The Quarterly Journal of Economics*, 1992, *107* (1), 35–78.

Klenow, Peter and Andrés Rodríguez-Clare, "The Neoclassical Revival in Growth Economics: Has It Gone Too Far?," in "NBER Macroeconomics Annual 1997, Volume 12" NBER Chapters, National Bureau of Economic Research, May 1997, pp. 73–114.

Krusell, Per, Lee E. Ohanian, José-Victor Ríos-Rull, and Giovanni L. Violante, "Capital-Skill Complementarity and Inequality: A Macroeconomic Analysis," *Econometrica*, September 2000, *68* (5), 1029–1054.

Lagakos, David, Benjamin Moll, Tommaso Porzio, Nancy Qian, and Todd Schoellman, "Life-Cycle Human Capital Accumulation Across Countries: Lessons From U.S. Immigrants," NBER Working Papers 21914, National Bureau of Economic Research January 2016.

_ , _ , _ , _ , and _ , "Life-Cycle Wage Growth across Countries," *Journal of Political Economy*, 2017.

Lemieux, Thomas, "The "Mincer Equation" Thirty Years After Schooling, Experience, and Earnings," in Shoshana Grossbard, ed., *Jacob Mincer A Pioneer of Modern Labor Economics*, Springer US, 2006, pp. 127–145.

Machin, Stephen and John Van Reenen, "Technology and Changes in Skill Structure: Evidence from Seven OECD Countries," *The Quarterly Journal of Economics*, 1998, *113* (4), 1215–1244.

Malmberg, Hannes, "How does the efficiency of skilled labor vary across rich and poor countries? An analysis using trade and industry data," Working Paper 2018.

Mayer, Thierry and Soledad Zignago, "Notes on CEPII's distances measures: The GeoDist database," Working Papers 2011-25, CEPII Research Center December 2011.

Minnesota Population Center, "Integrated Public Use Microdata Series, International: Version 7.2 [dataset]," `https://doi.org/10.18128/D020.V7.2` 2019.

Oberfield, Ezra and Devesh Raval, "Micro Data and Macro Technology," NBER Working Papers 20452, National Bureau of Economic Research, Inc September 2014.

OECD, *The Survey of Adult Skills* 2016.

Okoye, Dozie, "Appropriate Technology and Income Differences," *International Economic Review*, 2016, *57* (3), 955–996.

Ruggles, Steven, Sarah Flood, Ronald Goeken, Josiah Grover, Erin Meyer, Jose Pacas, and Matthew Sobek, "IPUMS USA: Version 9.0 [dataset]," `https://doi.org/10.18128/D010.V9.0` 2019.

Schoellman, Todd, "Education Quality and Development Accounting," *Review of Economic Studies*, 2012, *79* (1), 388–417.

_ , "Early Childhood Human Capital and Development," *American Economic Journal: Macroeconomics*, July 2016, *8* (3), 145–174.

World Bank, *World Development Indicators 2017*, The World Bank, 2017.

Tables

Table I: Skill Premium, Supply and Efficiency across Countries

	Baseline			No Hours	All Working Age	Traditional
Country	w_H/w_L	$\tilde{H}/\tilde{L}$	$(A_H Q_H)/(A_L Q_L)$	$(A_H Q_H)/(A_L Q_L)$	$(A_H Q_H)/(A_L Q_L)$	$(A_H Q_H)/(A_L Q_L)$
India	2.230	0.205	0.041	0.050	0.092	0.040
Indonesia	1.957	0.070	0.003	0.004	0.009	0.006
Jamaica	2.969	0.067	0.010	0.011	0.011	0.003
Brazil	3.419	0.158	0.087	0.121	0.115	0.022
Venezuela	2.490	0.257	0.089	0.132	0.152	0.055
Uruguay	2.218	0.363	0.126	0.189	0.225	0.260
Panama	2.262	0.313	0.099	0.123	0.119	0.077
Mexico	2.205	0.227	0.049	0.069	0.070	0.040
Trinidad and Tobago	2.746	0.100	0.018	0.022	0.024	0.009
Israel	1.606	0.596	0.129	0.155	0.109	0.156
Canada	1.508	1.539	0.711	0.825	0.928	1.628
United States	1.802	1.397	1	1	1	1
Elasticity wrt GDP p.w.	-0.138	0.911	1.408	1.366	1.117	1.575
	[0.078]	[0.244]	[0.394]	[0.402]	[0.414]	[0.509]

Notes: The Table shows the skill premium, relative skill supply and efficiency across the countries in the micro-data sample. Relative skill efficiency is normalised such that it takes value 1 for the United States. *No Hours* refers to estimates obtained when not weighting workers by hours worked; *All Working Age* refers to estimates obtained when including all working age population irrespective of employment status (and hours worked); *Traditional* refers to estimates obtained when using a Mincerian return of 0.10 to impute the skill premium and calibrate the human capital stocks. The last row shows the coefficient of a regression of the log of each variable on log GDP per capita (standard errors in brackets).

Table II: Skill Premium, Supply and Efficiency across Countries - Robustness

	θ_W	$\theta_{\tilde{H}/\tilde{L}}$	θ_{AQ}		
			$\sigma = 1.5$	$\sigma = 1.3$	$\sigma = 2$
(1) Baseline	-0.138	0.911	1.408	2.439	0.635
	[0.078]	[0.244]	[0.394]	[0.666]	[0.194]
(2) Experience and Gender	-0.024	0.796	1.520	2.549	0.748
	[0.086]	[0.249]	[0.398]	[0.673]	[0.199]
(3) Baseline (Self-Employment Sample)	-0.412	1.413	1.590	2.925	0.589
	[0.089]	[0.356]	[0.633]	[1.062]	[0.315]
(4) Self-Employment	-0.412	1.384	1.533	2.830	0.561
	[0.087]	[0.366]	[0.639]	[1.077]	[0.315]
(5) Agriculture	-0.274	1.459	1.719	2.858	0.770
	[0.106]	[0.366]	[0.466]	[0.753]	[0.234]
(6) Manufacturing	-0.209	0.900	0.952	1.615	0.399
	[0.103]	[0.272]	[0.265]	[0.446]	[0.126]
(7) Low-Skill Services	-0.159	0.843	0.992	1.649	0.444
	[0.105]	[0.316]	[0.359]	[0.589]	[0.176]
(8) High-Skill Services	-0.016	0.530	0.850	1.345	0.438
	[0.081]	[0.268]	[0.360]	[0.575]	[0.186]

Notes: The Table shows the elasticities of the skill premium, relative skill supply and relative skill efficiency with respect to GDP per worker (standard errors in brackets). The elasticities are computed using data for the 12 countries in the micro-data sample, with the exceptions of rows (3)-(4) for which only the 8 countries with self-employment data are used.

Table III: Relative Human Capital across Countries

	Broad Sample ($N = 104$)				Micro-Data Sample ($N = 12$)			
	θ_Q	θ_Q/θ_{AQ}			θ_Q	θ_Q/θ_{AQ}		
		$\sigma = 1.5$	$\sigma = 1.3$	$\sigma = 2$		$\sigma = 1.5$	$\sigma = 1.3$	$\sigma = 2$
(1) US Immigrants	0.105	0.095	0.057	0.189	0.043	0.030	0.018	0.068
	[0.016]				[0.048]			
(2) All Host Countries	0.098	0.088	0.053	0.176	0.078	0.055	0.032	0.123
	[0.016]				[0.047]			
(3) Bilateral Controls	0.062	0.056	0.034	0.112	0.095	0.067	0.039	0.149
	[0.026]				[0.087]			
Robustness (US Immigrants)								
(4) Selection Adjusted	0.039	0.035	0.021	0.070	0.067	0.047	0.027	0.105
	[0.026]				[0.080]			
(5) 10+ Years in US	0.065	0.059	0.035	0.118	0.078	0.055	0.032	0.122
	[0.017]				[0.060]			
(6) English Speakers	0.096	0.087	0.052	0.173	0.039	0.028	0.016	0.061
	[0.015]				[0.041]			
(7) Skill Downgrading	0.072	0.065	0.039	0.130	0.007	0.005	0.003	0.012
	[0.014]				[0.038]			
(8) Sorting (Sectors)	0.094	0.085	0.051	0.170	0.078	0.056	0.032	0.123
	[0.012]				[0.037]			
(9) Sorting (Geographic)	0.101	0.091	0.055	0.182	0.033	0.024	0.014	0.052
	[0.016]				[0.044]			

Notes: The Table shows the elasticity of relative human capital with respect to GDP per capita θ_Q (standard errors in brackets) and its ratio with respect to the elasticity of relative skill efficiency θ_{AQ}. Each row reports results from a different methodology (as indicated by the row titles) to estimate the relative human capital endowment of high-skill labor.

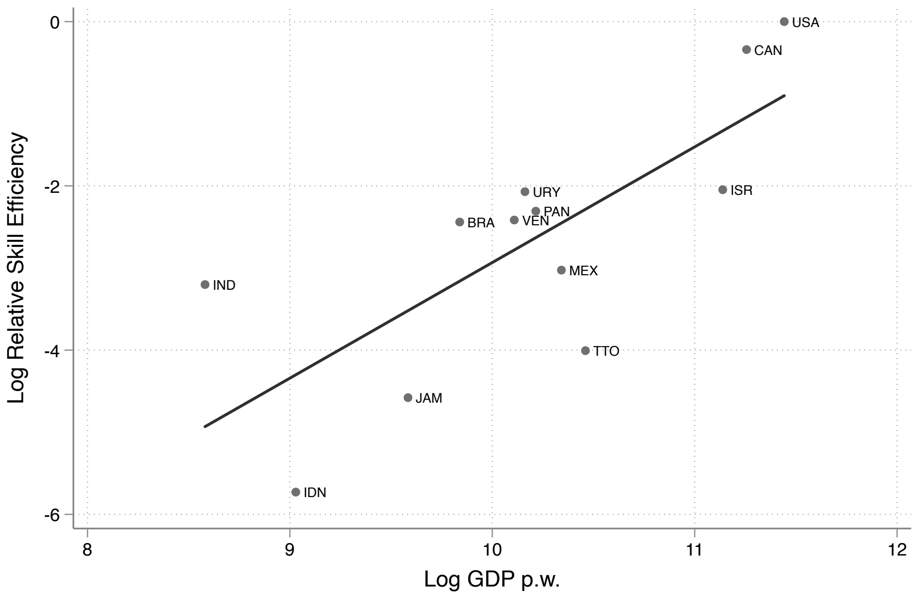
Table IV: Relative Human Capital and Development Accounting - US vs India

	Counterfactual Relative GDP (US=1)			
	$\sigma = 1.5$	$\sigma = 2$	$\sigma = 4$	$\sigma = \infty$
Relative Human Capital Interpretation				
(1) $\theta_Q = \theta_{AQ}$	0.698	0.289	0.161	0.120
Relative Technology Interpretation				
(2) $\theta_Q = 0$	0.104	0.112	0.126	0.140
Migrant-Based Calibration				
(3) $\theta_Q = 0.055$	0.112	0.123	0.140	0.158
(4) $\theta_Q = 0.05 \times \theta_{AQ}$	0.112	0.117	0.127	0.139

Notes: The Table shows the counterfactual GDP ratio 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. For comparison, the actual GDP ratio in the data is $y_P/y_R = 0.057$.

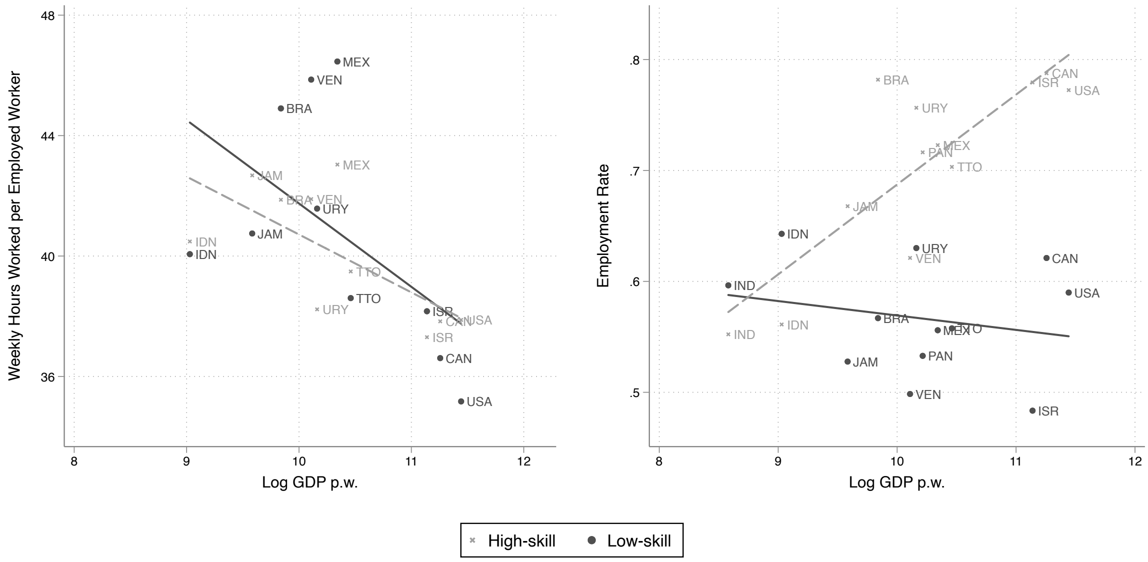
Figures

Figure I: Relative Skill Efficiency across Countries



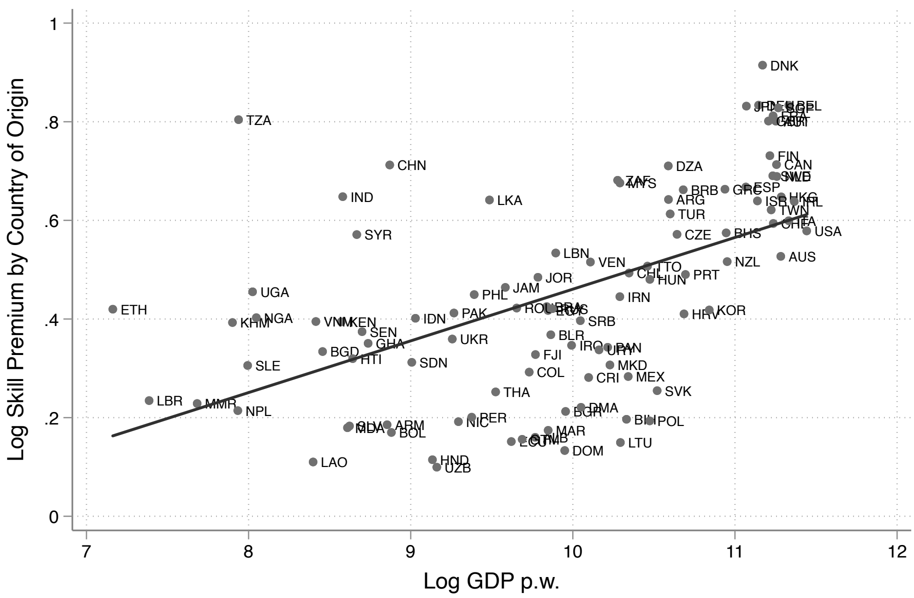
Notes: The figure plots log relative skill efficiency and log GDP per worker for the 12 countries in the micro-data sample. Relative skill efficiency is normalized to take value 1 (0 in log) for the United States. The solid line represents the best linear fit.

Figure II: Hours Worked and Employment Rate by Skill Level



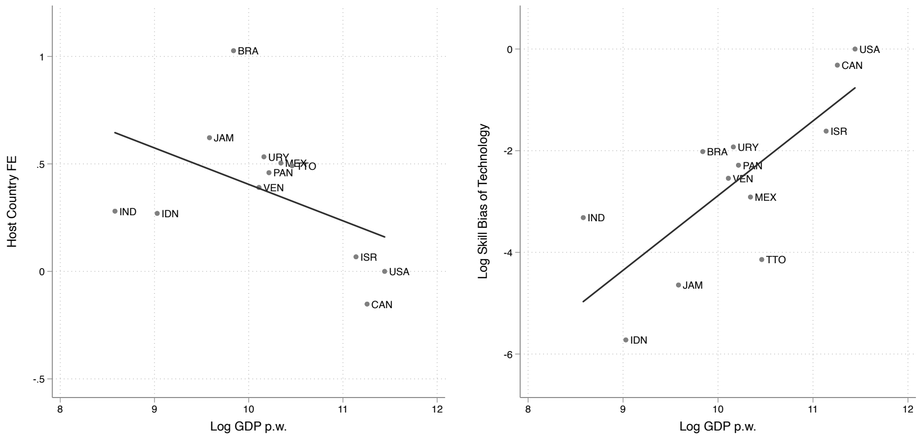
Notes: The figure plots the skill-specific average weekly hours per employed worker (left panel) and employment rate (right panel) against log GDP per worker for the countries in the micro-data sample. The left panel does not include India and Panama, as no data on hours worked is available for these countries. The solid (dashed) line represents the best linear fit for the low-skill (high-skill) group.

Figure III: Skill Premia and Country of Origin's GDP - US Immigrants



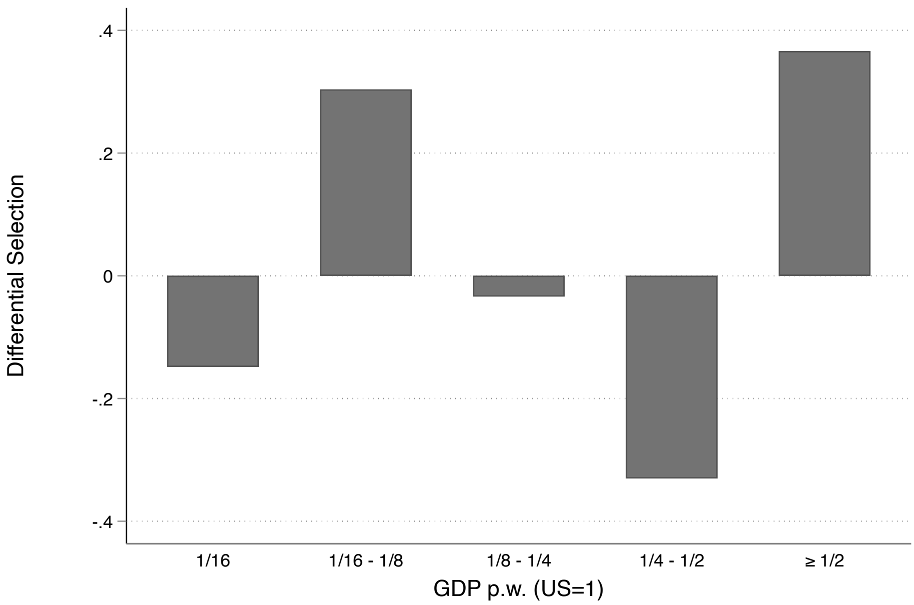
Notes: The figure plots the log skill premium across US immigrants' countries of origin, against the log GDP per worker in the country of origin. The solid line shows the best linear fit.

Figure IV: Host Country Fixed Effects and Skill Bias



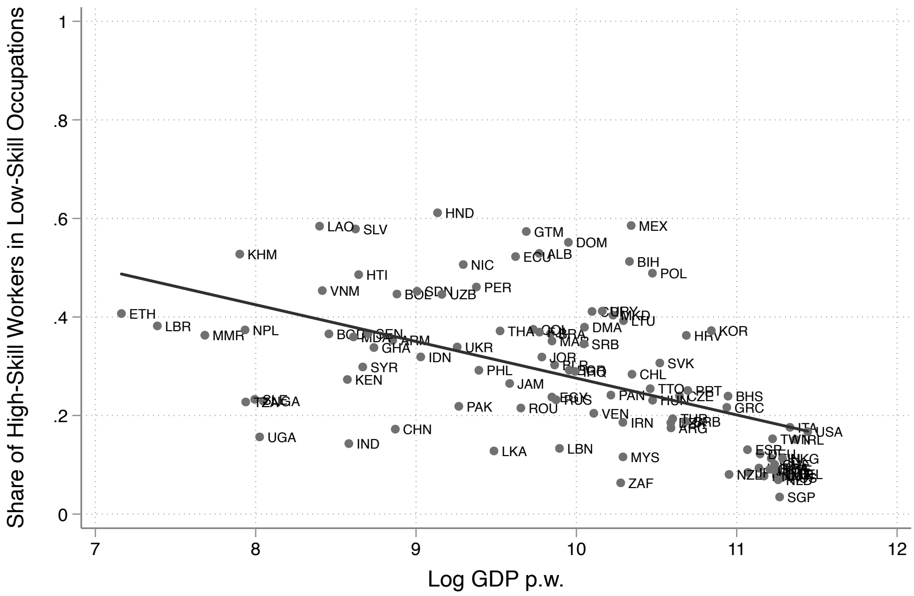
Notes: The left graph plots the host country fixed effect estimated from from equation (17) against log GDP per worker. The right graph plots the log skill bias of technology implied by the host country fixed effect against log GDP per capita. Both the host country fixed effect and the skill bias of technology are normalised such that they take value 1 (0 in logs) for the United States. The solid lines show the best linear fits.

Figure V: Differential Selection of High- and Low-Skill Emigrants



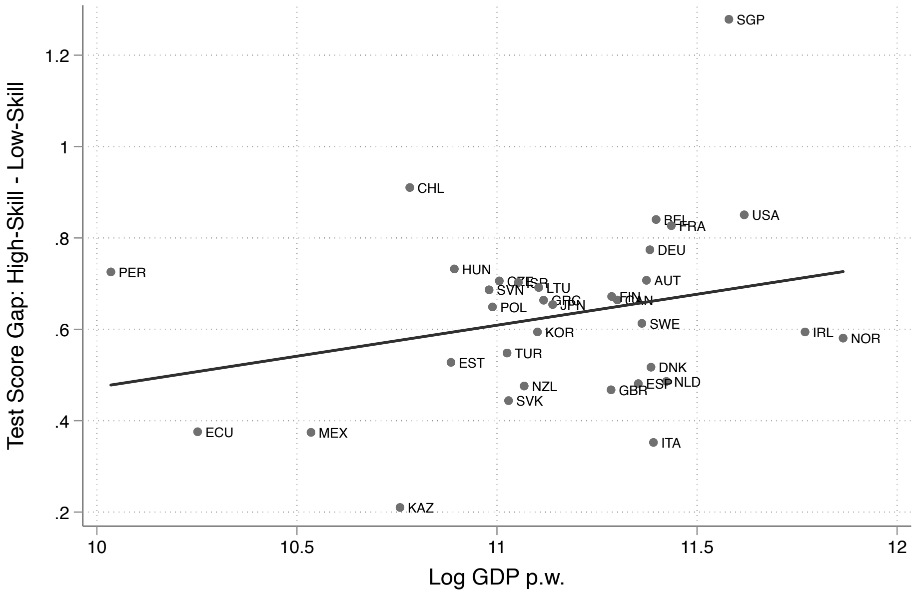
Notes: The figure plots the measure of differential selection of high-skill (college educated) and low-skill (high school educated) emigrants from Hendricks and Schoellman (2018), by levels of GDP per worker.

Figure VI: Skill Downgrading across Countries of Origin



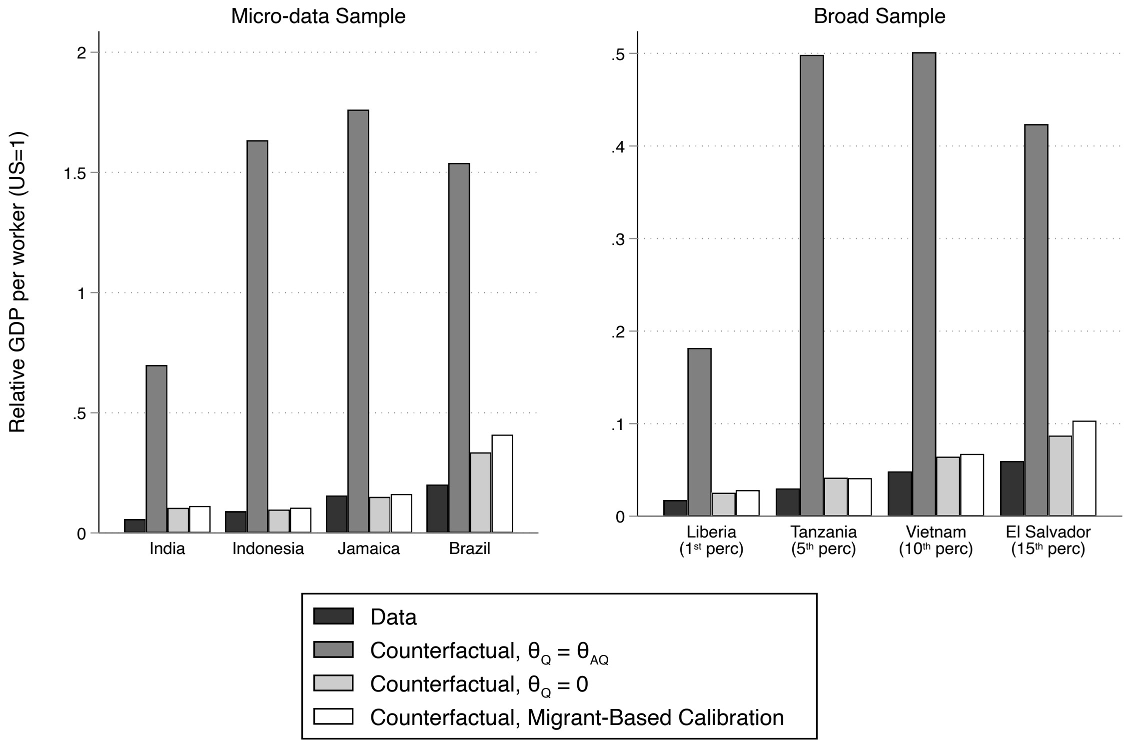
Notes: The figure plots the share of high-skill workers employed in low-skill occupations against the log GDP per worker of the country of education. High-skill workers are defined as workers with at least some tertiary education. High-skill occupations are defined as occupations where at least 50% of the employed natives are high-skilled. The solid line represents the best linear fit.

Figure VII: Relative Human Capital - PIAAC Scores



Notes: The figure plots the difference between the average PIAAC numeracy score of high-skill (college educated) and low-skill (high school educated) workers against log GDP per worker in 2014. Scores are standardized to have an (individual-level) average of 0 and a standard deviation of 1 when pooling all countries. The solid line represents the best linear fit.

Figure VIII: Relative Human Capital and Development Accounting - Selected Countries



Notes: The figure plots the actual value (black bars) and various counterfactuals for the GDP per worker ratio with respect to the US.