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

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Abstract

This paper studies how the relative efficiency of high- and low-skill labor varies across countries. I use micro data for countries at different stages of development to document that the skill premium varies little between rich and poor countries, despite large differences in the relative skill supply. This fact is not explained by cross-country differences in sectoral composition, incidence of self-employment or returns to other individual-level characteristics, and is consistent with the view that highly educated workers are relatively more productive in rich countries. I propose a methodology based on the comparison of labor market outcomes of immigrants with different levels of educational attainment 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 than the latter.

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1 Introduction

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; Malmberg, 2017). 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.

Different 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 “technology view”). This might be because firms in rich countries adopt technologies more suitable for skilled workers, as proposed in Caselli and Coleman (2006) and Caselli (2016), 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 postulated 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 “human capital view”). Distinguishing between these two broad interpretations has important implications for various open questions in macro-development, such as the degree of transferability of technology
across space and the role of human capital in accounting for cross-country gaps in economic performance.

In this paper I re-examine the measurement and interpretation 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 propose an approach based on the analysis of US immigrants to separately identify the role of technology and human capital in explaining the cross-country variation in relative skill efficiency.

The measurement contribution of the paper consists in the construction of more 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. In this paper, 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 implied 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, the 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 also re-visit with my data several variations to the production function setup considered in previous work (such as capital-skill complementarity, different definitions of high- and low-skill labor and different degrees of substitutability between the two) and show that, while naturally affecting magnitudes, they do not change the substance of the conclusion that relative skill efficiency is higher in rich countries.

I then study the sources of this gap. My approach is based on the analysis of US immigrants, 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. I then show that in this setting comparing skill premia across immigrants’ countries of origin provides a way to isolate cross-country differences in relative human capital. Intuitively, for migrants exposed to an equally skill-biased technological and institutional environment, cross-nationality differences in the skill premium identify differences in the relative human capital endowment of high- and low-skill labor.

I find that the relative human capital of skilled labor accounts for a minor share - 5% to 16%, with a baseline estimate of 8% - 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 US immigrants 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 US local labor markets. I provide evidence 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 endowment.

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). Recent work by Malmberg (2017) 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) the development of a methodology to discriminate between human capital and technology as sources of these gaps.¹ This distinction mirrors, on a cross-country dimension, a related debate on the relative roles of technology and human capital in explaining the rise of the skill premium over time (Acemoglu, 1998, 2002; Bowlus and Robinson, 2012; Hendricks and Schoellman, 2014).

This paper is also closely related to a growing literature studying the labor market experience of immigrants to learn about cross-country differences in human capital (Schoellman, 2012, 2016; Lagakos et al., 2016; Hendricks and Schoellman, 2018, 2019). The key difference between this line of work and the exercise in the second part of my paper is one of focus: while these papers study the role of average human capital per worker in explaining output gaps, I quantify the role of the relative human capital endowment of high- and low-skill workers in explaining differences in relative skill efficiency. As I discuss in Section 6, the answers to these research questions are mutually informative and, when combined, provide a more comprehensive understanding of the cross-country variation in human capital and technology.

The paper is structured as follows. Section 2 describes the data I use in this study. Section 3 introduces the basic framework and describes the measurement of relative skill efficiency. Section 4 shows evidence on immigrants, while Section 5 discusses potential identification

¹See also Caselli and Ciccone (2019) and Jones (2019) for a recent exchange discussing these two possible interpretations.
concerns and alternative interpretations for the results. Section 6 frames the results in the context of the development accounting literature, and Section 7 concludes by discussing some implications and possibilities for future work.

2 Data

I consider two samples of countries, which I rely on at different stages of the analysis. First, a sample of 12 countries with detailed micro-data available, for the measurement part of the paper (the “micro-data sample”). Second, a broader sample of 65 countries with a large number of emigrants observed in the US, which I use to quantify the role of human capital endowment for the cross-country variation in relative skill efficiency (the “broad sample”).

For the micro-data sample, I use a collection of Census data harmonized by IPUMS and IPUMS International (Ruggles et al., 2019; Minnesota Population Center, 2019). I consider all countries with available information on wages or earnings, education, labor market status, gender, experience and sector of employment. This leaves 12 countries in 2000 or a close year, 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. All the considered Censuses are nationally representative. Moreover, the IPUMS team actively works to ensure a high level of comparability across countries. Previous studies using these or related data for cross-country comparisons include Herrendorf and Schoellman (2018) and Lagakos et al. (2017).

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 aiming to address the implications for my inference of the higher prevalence
of self-employment in poorer countries. 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 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.

The broad sample includes 65 countries with at least 300 foreign-born and foreign-educated individuals in the US Census, satisfying a number of sample restrictions discussed in Section 4. For these countries, I use the educational attainment data in Barro and Lee (2013) to construct the relative supply of skilled labor. Real GDP per worker for all countries comes from the Penn World Table (Feenstra et al., 2015).

3 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.

3.1 Framework

Throughout the paper, I consider variants of the production technology

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

where $c$ indexes countries, $K_{c,c}$ is physical capital and $X_{1,c}, \ldots, X_{N,c}$ 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 parameters, 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

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

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 the 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, I think of $Q_{1,c}, \ldots, Q_{N,c}$ as capturing 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. The main question of interest for my analysis is how the relative efficiency units provided by more and less skilled workers varies across countries.

Let’s consider any two types of workers indexed by $H$ and $L$. Under perfectly competitive labor markets, the wage ratio is

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

i.e. the product between 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 (1) 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 consider several alternatives in the following ones.
3.2 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,

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

where the human capital aggregator \( G \) is given by

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

Here, \( H_c \) and \( L_c \) denote high-skill and low-skill labor services, and \( \sigma \) 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

\[ H_c = Q_{H,c} \hat{H}_c \]  
\[ L_c = Q_{L,c} \tilde{L}_c \]

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

\[ \frac{w_{H,c}}{w_{L,c}} = \left( \frac{A_{H,c}Q_{H,c}}{A_{L,c}Q_{L,c}} \right)^{\frac{\sigma-1}{\sigma}} \left( \frac{\hat{H}_c}{\tilde{L}_c} \right)^{-\frac{1}{\sigma}} \]

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. I take 2000 as my baseline year,
and consider data sources relative to (or as close as possible to) this date.

**Implementation.** To bring this framework to the data, two key choices to be made are the assignment of workers to the high- and low-skill categories and the calibration of the elasticity $\sigma$. 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 3.3.

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

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

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

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 $m \in \mathcal{L} = \{\text{primary, lower secondary, upper secondary}\}$. For each country, I run a log-wage regression with the 5 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

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2The 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 backgounding 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 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.
\(\frac{w_H}{w_L}\) 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.

**Comparison with Traditional Measurement.** At this point it is useful to remind the reader of the key differences between the approach illustrated above and 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.** With the country-specific estimates of \(\frac{\tilde{H}_c}{\tilde{L}_c}\) and \(\frac{w_H}{w_L}\) at hand, I can back out \(\frac{A_{H,c}Q_{H,c}}{A_{L,c}Q_{L,c}}\) from (4). 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 two rows report the elasticities of each variable with respect to GDP per worker and the relative supply of skilled labor.

[Table I here]

The skill premium is on average lower 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]

This result is driven by the fact that the relationship between the skill premium and the relative supply of skilled workers is not very steep, so that a high efficiency of skilled labor in skill-abundant countries is needed to fit the data. Equation (4) shows that in a world where \( \log \frac{A_{H,c}Q_{H,c}}{A_{L,c}Q_{L,c}} \) was constant across countries (or, more generally, uncorrelated with \( \log \frac{H}{L} \)), the elasticity of the skill premium with respect to the relative supply would be \( -1/\sigma = -0.66 \). The estimated elasticity is only one third of that (-0.17, with a standard error of 0.05). This implies that, to fit the data, \( \frac{A_{H,c}Q_{H,c}}{A_{L,c}Q_{L,c}} \) must increase with \( \frac{H}{L} \), attenuating the negative relationship between the latter and the skill premium. To give an example, if all countries had the US level of relative skill efficiency, the model would predict for India a skill premium of 6.48, while the actual one is 2.23.

The last three columns of Table I illustrate and deconstruct the differences with the traditional approach for measuring relative skill efficiency. Column 4 and column 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 a slight 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. The left panel shows that, 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. The right panel shows that the employment rate is increasing with GDP per worker.
for the high-skill, and decreasing for the low-skill. Overall, this implies that the relative labor supply of working-age high- and low-skill individuals is higher in rich countries. This pattern is consistent with the evidence reported in Bick et al. (2016) for a different and broader 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 across countries 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 C 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. As I document in the Appendix, 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.

3 I use the WDI data on schooling duration to impute the years of schooling corresponding to each level of educational attainment.
3.3 Robustness

In this section I subject the result that relative skill efficiency is higher in rich countries to six robustness checks. The first three are made possible by the availability of micro-data on various worker characteristics and, to my knowledge, have not been studied in previous work. The remaining three concern the specification of the production technology, and have been considered in Caselli and Coleman (2006) and Jones (2014a), among others. I then conclude the section by highlighting further variations to the baseline setup that might in principle help explaining the variation in relative skill efficiency, but for which the existing evidence is insufficient for proper quantifications.

3.3.1 Experience and Gender

This section measures relative skill efficiency 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). A natural question is whether differences in the relative quantities or returns of these characteristics can explain the result that high-skill labor is relatively more productive in rich countries.

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

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

(7)

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

(8)

where $w_{H,c,n,\exp,g}$, $w_{L,c,m,\exp,g}$, $\tilde{H}_{c,n,\exp,g}$ and $\tilde{L}_{c,m,\exp,g}$ denote the wages and total hours worked.
by high- and low-skill workers with experience $\exp$, gender $g$ and education levels $n$ and $m$, with $\exp \in \mathcal{E} = \{0$ to $4, 5$ to $9, 10$ to $14, 15$ to $19, 20$ to $24, 25$ to $29, 30$ to $34, 35$ to $39, 40$ or more$\}$ and $g \in \mathcal{G} = \{\text{male, female}\}$. Given that sample sizes are sometimes small at the education $\times$ experience $\times$ gender level, I assume that within skill levels the effects of these characteristics on log wages are not interactive, so that one can write

$$
\frac{w_{H,c,n,\exp,g}}{w_{H,c,\text{tertiary},0\text{to}4,\text{male}}} = e^{\beta_{H,n} + \lambda_{H,\exp} + \mu_{H,g}} \tag{9}
$$

$$
\frac{w_{L,c,m,\exp,g}}{w_{L,c,\text{upper secondary},0\text{to}4,\text{male}}} = e^{\beta_{L,n} + \lambda_{L,\exp} + \mu_{L,g}} \tag{10}
$$

with the normalizations $\beta_{H,\text{tertiary}} = \lambda_{H,0\text{to}4} = \mu_{H,\text{male}} = 0$ and $\beta_{L,\text{upper secondary}} = \lambda_{L,0\text{to}4} = \mu_{L,\text{male}} = 0$. I estimate all parameters from log-wage regressions with educational, experience and gender dummies (interacted with skill level) as controls, and I calculate the skill premium as the wage ratio between baseline high- and low-skill workers. With the estimates of the relative supply and the skill premium at hand, I calculate relative skill efficiency from (4).

Table II shows the results. Compared to the baseline estimates in Table I, both the skill premium 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 compared to Table I. Overall, these results suggest that cross-country gaps in relative skill efficiency are not due to composition effects in terms of experience and gender.

[Table II here]

### 3.3.2 The Role of Self-Employment

As it is well known, self-employment is more widespread in poor countries compared to rich countries. While the self-employed do 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.
For some of the countries in the micro-data sample, namely Brazil, Canada, Israel, Mexico, Panama, Trinidad and Tobago, United States and Venezuela, the Census I use includes information on self-employment income. As discussed in Herrendorf and Schoellman (2018), using self-employment income in lieu of wage income is problematic as self-employment income accrues in principle 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 overestimated 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.

Table III shows the results. Indeed, in most countries the estimated skill premium is larger when the self-employed are included, and this marginally reduces the cross-country gaps in relative skill-efficiency. However, the magnitude of this correction is small, and most of the gaps persist nevertheless.

3.3.3 Skill Efficiency across Sectors

The individual-level information available for the micro-data sample allows me to study the variation of relative skill efficiency at the sector level. This is potentially important, as the production technology is plausibly different across sectors, and at the same time rich and poor countries differ dramatically in their sectoral composition of employment. In this section, I examine the extent to which the cross-country variation in “aggregate” relative skill efficiency is driven by sectoral composition as opposed to within-sector differences.

To do so, I postulate a sector-level production function. Suppose the production technology for sector $s$ in country $c$ is

$$Y_{c,s} = F_{c,s} \left( K_{c,s}, \left[ (A_{H,c,s} H_{c,s})^{\frac{\sigma - 1}{\sigma}} + (A_{L,c,s} L_{c,s})^{\frac{\sigma - 1}{\sigma}} \right]^{\frac{1}{\sigma - 1}} \right)$$
where the sector-level elasticity of substitution is denoted by $\tilde{\sigma}$ (to distinguish it from the aggregate elasticity $\sigma$). The elasticity is assumed to be the same across countries and sectors. The skill premium in sector $s$ is given by

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

As for the aggregate case, sector-specific relative skill efficiencies can be backed out using sector-specific skill premia and human capital 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). I separate low- and high-skill services in light of the large heterogeneity among services sub-sectors in terms of skill intensity and productivity (Duarte and Restuccia, 2019).

One complication arises from the fact that estimates of the aggregate elasticity of substitution, such as the ones in Ciccone and Peri (2005), are in principle not directly informative on the corresponding elasticity at the sector level. If sectors differ in their 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. Depending on the degree of heterogeneity across sectors and on the magnitude of this reallocation effect, the aggregate elasticity might be smaller or larger than the sector-level one (Oberfield and Raval, 2014).

To calibrate $\tilde{\sigma}$, I rely on the theoretical results in Oberfield and Raval (2014), who derive a general mapping between the aggregate and the micro-level elasticities of substitution among two factors of production. Their results imply that the aggregate elasticity of substitution $\sigma$ can be written as a convex combination of the sector-level elasticity, $\tilde{\sigma}$, and a term capturing the magnitude of the reallocation effect

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

(11)
where $\chi \in [0, 1]$ is a measure of cross-sector heterogeneity in skill intensity, $\tilde{\alpha}$ and $\tilde{\zeta}$ are weighted averages of the sectoral capital shares and elasticities of substitution between capital and labor, and $\epsilon$ is the demand elasticity of substitution between sectors (the expressions for $\chi$, $\tilde{\alpha}$ and $\tilde{\zeta}$ are provided in Appendix D). Conditional on US specific values for $\chi$, $\tilde{\alpha}$, $\tilde{\zeta}$ and $\epsilon$, I can back out the value of $\tilde{\sigma}$ that is consistent with $\sigma = 1.5$, as estimated in the literature based on US data. The computation of the heterogeneity index yields $\chi = 0.925$, which implies that the sector-level elasticity is in fact close to the aggregate one, and largely insensitive to the values of $\tilde{\alpha}$, $\tilde{\zeta}$ and $\epsilon$. I set $\tilde{\alpha} = 1/3$ and $\tilde{\zeta} = 1$, i.e. sectoral Cobb-Douglas production functions with capital shares of 1/3, and $\epsilon = 0$, as estimated in Herrendorf et al. (2013); the resulting sector-level elasticity is $\tilde{\sigma} = 1.59$.4

Table IV shows the estimated relative skill efficiencies across sectors, normalised so that the aggregate relative skill efficiency for the US is equal to 1. Three main conclusions stand out. First, across all countries the efficiency gap between high- and low-skill labor is highest in high-skill services and lowest in agriculture, with manufacturing and low-skill services displaying intermediate values.5 Second, relative skill efficiency is strongly increasing in GDP per worker across all sectors. Third, the cross-country gap is largest in agriculture (the least skill-intensive sector) and smallest in high-skill services (the most skill-intensive sector).

[Table IV here]

The fact that large cross-country differences are observed across all sectors suggests that sectoral composition is not the main driver of the dispersion in relative skill efficiency. However, the patterns of cross-sectoral differences leave open the possibility that sectoral composition might play some role: for both high- and low-skill workers, poor countries tend to have higher employment shares in sectors where the relative efficiency of high-skill labor is lower, such as agriculture (sectoral employment shares by education level are reported in Appendix D).

4Given the high value of $\chi$, reasonable deviations from these assumptions have minimal impact on the calibrated $\tilde{\sigma}$. For example, using the sector-specific capital shares and elasticities of substitution between capital and labor estimated in Herrendorf et al. (2015) leads to $\tilde{\sigma} = 1.60$ (for this calculation I impute the “services” values for both low- and high-skill services); using $\epsilon = 0.5$ as in Buera and Kaboski (2009) leads to $\tilde{\sigma} = 1.57$.

5As documented in Appendix D, this is primarily driven by the fact that the relative supply of high-skill labor is highest (lowest) in high-skill services (agriculture), while the skill premium is similar across sectors.
I conclude the discussion on sectoral composition with a simple counterfactual exercise. I ask the following question: how large would the cross-country variation in the inferred aggregate relative skill efficiency be, if all countries had the same sectoral shares of employment (by education) as the United States? In other words, to what extent would equalizing the sectoral composition (keeping fixed the sector-level relative efficiencies shown in Table IV, as well as the total number of high- and low-skill workers) close the cross-country gaps documented in Section 3.2?

Answering this question requires more structure on the productive and the demand sides of the economy. I outline the key steps of my approach here, and I provide a detailed discussion in Appendix D. To make progress, I impose four simplifying assumptions: (i) the sectoral production function is Cobb-Douglas, with equal capital shares across sectors, (ii) the prices of the goods produced in the different sectors are unaffected by the reallocation of employment across sectors (as for small open economies), (iii) labor and capital are not mobile across sectors, and (iv) for a given level of educational attainment, workers’ human capital does not vary across sectors. I denote $RSE_c$ the aggregate relative skill efficiency estimated when ignoring sectoral heterogeneity and postulating an aggregate production function

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

where $\frac{w_{H,c}}{w_{L,c}}$ and $\frac{\tilde{H}_c}{\tilde{L}_c}$ are constructed exactly as in Section 3.2, and $\sigma$ is the aggregate elasticity of substitution. I construct for each country a counterfactual allocation of high- and low-skill workers across sectors applying the US sectoral shares of employment by skill (in terms of both persons and hours). Using the expressions for equilibrium wages, I then compute the counterfactual skill premium $\frac{w_{C_H,c}}{w_{C_L,c}}$ and relative supply $\frac{\tilde{H}_C}{\tilde{L}_C}$ prevailing at the new allocation,
and the counterfactual aggregate relative skill efficiency:

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

The counterfactual aggregate relative skill efficiencies is displayed in the last column of Table IV. The elasticity with respect to GDP per worker is about 12% lower in the counterfactual compared to the baseline (column 1). This result confirms that while sectoral composition drives some of the cross-country variation, relative skill efficiency gaps are primarily a within-sector phenomenon.

3.3.4 Alternative Values of the Elasticity of Substitution

This section examines the robustness of the results to alternative calibrations of the elasticity of substitution between high- and low-skill labor. This is an important parameter for the computation of relative skill efficiency: the more substitutable high- and low-skill workers are, the less one needs to appeal to differences in relative efficiencies to rationalise the weak cross-country relationship between relative supply and relative wages.

I chose \( \sigma = 1.5 \) from Ciccone and Peri (2005) as baseline value since this paper provides credible identification by identifying sources of exogenous variation in the relative supply of skilled labor across US states. This value is not far from alternative estimates in the literature: 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 second and third columns of Table V show the results for the two extremes of this range. The magnitude of the cross-country differences in relative skill efficiency is quite sensitive to the value of the elasticity of substitution. However, even for \( \sigma = 2 \), gaps with respect to the US are large, ranging from a factor of 1.3 (Canada) to a factor of 17 (Indonesia).

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6Although the total number of high- and low-skill hours is kept fixed in the counterfactual, \( \frac{\tilde{H}^C_c}{L^C_c} \), differs from \( \frac{H^C_c}{L^C_c} \) because the new sectoral allocation of employment affects the relative wages used for the conversion of high-skill (low-skill) workers into tertiary (upper secondary) educated equivalents. In practice, these effects are small, and most of the difference between \( RSE_c \) and \( RSE^C_c \) is driven by the adjustment of the skill premium. I refer to the Appendix for a more detailed illustration.
3.3.5 Alternative Skill Thresholds

The choice of which workers belong to the high- and low-skill groups is inevitably somewhat arbitrary. While part of macro-development literature has considered secondary educated workers high-skill (Caselli and Coleman, 2006), in labor economics the contraposition is often cast in terms of high-school and college graduates. The third and fourth columns of Table V show the results for two alternative skill thresholds: upper secondary and completed tertiary. Since rich countries have on average more high-school graduates than poor countries, considering them high-skill exacerbates the cross-country variation in the relative supply of high-skill labor, therefore leading to a larger dispersion in inferred relative skill efficiency (column 4). Instead, including only college graduates in the high-skill group somewhat reduces the slope of the relationship between relative skill efficiency and GDP per worker, and adds considerable noise to it (column 5). Even in the latter case, the gaps between the United States and the poorer countries in the sample remain substantial.

3.3.6 Capital-Skill Complementarity

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

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

where $\sigma$ is the elasticity of substitution between low-skill labor and high-skill labor (or equipment) and $\eta$ is the elasticity of substitution between high-skill labor and equipment. This production function displays capital-skill complementarity if $\sigma > \eta$, i.e. if equipment is more

---

7When the upper secondary educated are included in the high-skill group, I take the lower secondary educated as baseline low-skill workers.
substitutable with low-skill labor. The skill premium can be written as

$$\frac{w_{H,c}}{w_{L,c}} = \left[ 1 + \left( \frac{A_{K,c}K^E_e}{A_{H,c}Q_{H,c}H_c} \right)^{\frac{\eta-1}{\eta}} \right]^{\frac{\sigma-\eta}{\eta}} \left( \frac{A_{H,c}Q_{H,c}}{A_{L,c}Q_{L,c}} \right)^{\frac{\eta-1}{\eta}} \left( \frac{H_c}{L_c} \right)^{-\frac{1}{\sigma}}$$ (12)

Equation (12) illustrates how capital-skill complementarity affects my inference on relative skill efficiency. If $\sigma > \eta$ - the empirically relevant case according to Krusell et al. (2000)’s estimates - the skill premium is increasing in the ratio between effective equipment and high-skill labor, everything else equal. If rich countries are relatively abundant in equipment, capital-skill complementarity reduces the variation in $\frac{A_{H,c}Q_{H,c}}{A_{L,c}Q_{L,c}}$ needed to rationalise a relatively flat skill premium across countries. In a sense, this mechanism can be seen as a particular underpinning of skill-biased technological differences across countries: rich countries are relatively more abundant in the type of capital that is more complementary to high-skill labor.

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

$$\frac{rK^E_e}{w_{H,c}H_c} = \left( \frac{A_{K,c}K^E_e}{A_{H,c}Q_{H,c}H_c} \right)^{\frac{\eta-1}{\eta}}$$

which implies that the capital-skill complementarity term in (12) can be quantified with (i) data on the relative income share of equipment and high-skill labor, and (ii) a calibrated value for $\eta$. I use data from the Penn World Tables and IPUMS to construct the former (see Appendix A for the details), and Krusell et al. (2000)’s estimate of $\eta = 0.67$ for the latter. I then calculate the residual $\frac{A_{H,c}Q_{H,c}}{A_{L,c}Q_{L,c}}$ from equation (12), using the skill premia and labor stocks discussed in Section 3.

The last column of Table V show the results. The elasticity of $\frac{A_{H,c}Q_{H,c}}{A_{L,c}Q_{L,c}}$ with respect to GDP per worker is about half of the baseline one. The capital-skill complementarity term in (12) is larger for rich countries, which are relatively more abundant in equipment; this term is absorbed by the baseline estimates in column 1, while it is netted out in column 6. Overall, this result suggests that the relative abundance of equipment can in principle account for a
sizable part for the cross-country variation in relative skill efficiency.

3.3.7 Other Possibilities

The robustness checks considered so far do not exhaust the set of possible variations to the production function setup that would affect the inferred magnitude or the interpretation of relative skill efficiency gaps across countries. For example, a lower elasticity of substitution (while still greater than 1) in poor countries could rationalize large cross-country differences in the relative skill supply and small cross-country differences in the skill premium without appealing to large gaps in relative skill efficiency. Moreover, as pointed out in Jones (2014a,b), a greater degree of task specialization of high-skill workers in rich countries could make them relatively more productive even in absence of cross-country differences in the skill bias of technology, educational quality or selection into higher education. Finally, other compositional effects, such as those stemming from high- and low-skill workers sorting into different kinds of firms across countries, might contribute to the cross-country dispersion in “aggregate” relative skill efficiency.

While these are all intriguing possibilities, the existing evidence (including the worker-level data used in this paper) does not allow a proper quantification of their importance. Progress in this direction might come from additional country-specific estimates of the elasticity of substitution and the comparative analysis of task- and firm-level data across countries. I leave these interesting extensions for future work.

4 Sources of Differences in Relative Skill Efficiency

The analysis of micro data for a number of countries at different levels of development supports the existence of large gaps in relative skill efficiency. This pattern does not appear to be an artifact of measurement issues. This naturally leads to the next question: what explains the variation in relative skill efficiency across countries? I propose a strategy to answer this question based on the analysis of immigrants educated in different countries and observed in the same labor market.
**Setup.** I first modify the baseline framework in Section 3.1 by introducing a new dimension of worker heterogeneity: the fact that some of them 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.

I assume that 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 form

$$Y_c = A_c F (A_{Kc} K_c, A_{Lc} L_c, A_{Hc} H_c)$$

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

$$H_c = \sum_a Q_{H,c}^a \tilde{H}_c^a$$  \hspace{1cm} (13)$$

$$L_c = \sum_a Q_{L,c}^a \tilde{L}_c^a$$  \hspace{1cm} (14)$$

where $\tilde{H}_c^a$ and $\tilde{L}_c^a$ are the numbers of (baseline equivalent) hours worked by high- and low-skill workers educated in country $a$ and employed in $c$, and $Q_{H,c}^a$ and $Q_{L,c}^a$ represent their human capital. 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 light of this, in what follows I refer to the human capital endowments and wages of natives as $Q_{H,c}$, $Q_{L,c}$, $w_{H,c}$ and $w_{L,c}$.

In a competitive labor market, the wage ratio between high- and low-skill workers edu-
cated in country \( c \) is

\[
\frac{w_{H,c}^a}{w_{L,c}^a} = \frac{A_{H,c}Q_{H,c}^a F_H (A_{K,c}K_c, A_{L,c}L_c, A_{H,c}H_c)}{A_{L,c}Q_{L,c}^a F_L (A_{K,c}K_c, A_{L,c}L_c, A_{H,c}H_c)}
\] (15)

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 \( \frac{A_{H,c}}{A_{L,c}} \) and the same relative price of high-skill and low-skill efficiency units, but are endowed with different \( Q \)'s depending on their country of origin. By comparing skill premia across origin countries one can therefore isolate cross-nationality differences in the relative human capital of high- and low-skill labor. Under the additional assumption (discussed in greater detail below) that high- and low-skill migrants are not differentially selected from the corresponding populations in their country of origin, I can use these estimates to quantify the cross-country variation in relative human capital.

**Implementation.** I now describe how I map this framework to the data. I focus on the native and immigrant workers employed in the United States, observed in the IPUMS data. When computing wages, I implement the same sample restrictions as in Section 3.2 (16 to 65 years old wage-employed workers, working for at least 30 weeks and 30 hours per week in the previous year). Moreover, to isolate the role of the country of education, I only consider natives and immigrants likely to have completed their education before relocating to the US: as in Schoellman (2012), I restrict the sample to those who migrated at least six years after the age at which they should have ended their studies, given their level of educational attainment. When presenting the results, I focus on the 65 countries of origin for which I have at least 300 workers in the sample, after having implemented these restrictions.

I run a log-wage regression on educational dummies interacted with country of origin dummies, and calculate \( w_{H,c}^a \) and \( w_{L,c}^a \) as the exponentiated estimates corresponding to tertiary educated and upper secondary educated workers. To account for other factors affecting immigrants’ productivity in the US labor market, I include as additional controls a fourth degree polynomial in the number of years since migration and a self-reported level of English profi-
ciency (all interacted with country of origin dummies). With the country-of-origin-specific skill premia at hand, I identify the relative human capital endowment from

\[
\frac{w^a_{H,US}}{w^a_{L,US}} \div \frac{w_{H,US}}{w_{L,US}} = \frac{Q^H_{H,US}}{Q^L_{L,US}}
\]

where \( \frac{Q^H_{H,US}}{Q^L_{L,US}} \) is normalized to 1. I then use \( \frac{Q^H_{H,US}}{Q^L_{L,US}} \) as a proxy for \( \frac{Q^{H,a}_{H,a}}{Q^{L,a}_{L,a}} \) - possible issues with this being discussed in Section 5 - and compare the cross-country variation in this object to the overall cross-country variation in relative skill efficiency. I compute the latter using data on educational attainment from Barro and Lee (2013), imputing wages based on a Mincerian return of 10% common across countries (along the lines of the “traditional” approach described in Section 5). Given the estimates of \( \frac{Q_{H,c}}{Q_{L,c}} \) and \( \frac{A_{H,c} Q_{H,c}}{A_{L,c} Q_{L,c}} \), I back out the implied skill bias of technology \( \frac{A_{H,c}}{A_{L,c}} \).

To summarize, my empirical strategy is based on the comparison, within the United States, of the relative wages of high- and low-skill workers between the different countries where they were educated. I use cross-nationality gaps in migrants’ skill premia as proxies of the corresponding cross-country gaps in the relative human capital endowment of high-skill labor, and quantify the contribution of those in driving the dispersion in relative skill efficiency.

**Results.** As summary statistics for the cross-country variation, Table VI reports the elasticities of \( \frac{Q_{H,c}}{Q_{L,c}} \), \( \frac{A_{H,c}}{A_{L,c}} \), and \( \frac{A_{H,c} Q_{H,c}}{A_{L,c} Q_{L,c}} \) with respect to GDP per worker (the third being the sum of the first two). Since the magnitude of cross-country gaps in relative skill efficiency is quite sensitive to the assumed elasticity of substitution, as documented in Section 3.3, in addition to the baseline case with \( \sigma = 1.5 \), I also show results for \( \sigma = 1.3 \) and \( \sigma = 2 \), i.e. the lower and upper ends of the range of values estimated in the literature.

[Table VI here]
The first row reports the main results. The relative human capital endowment of high-skill labor is higher in rich countries, with an elasticity with respect to GDP per worker of 0.08. While positive and significant, this is small compared to the cross-country variation in relative skill efficiency. In this sample, the elasticity of the latter with respect to GDP per worker is about 1 for the baseline value of $\sigma$. This means that about 8% of the gap in relative skill efficiency between rich and poor countries can be accounted for by human capital, with the remaining 92% being driven by the skill bias of technology. Figure III visualizes this result: while both $\frac{Q_{H,c}}{Q_{L,c}}$ (left panel) and $\frac{A_{H,c}}{A_{L,c}}$ (right panel) are higher in rich countries, the cross-country variation in the latter is an order of magnitude larger. Setting a lower (higher) elasticity of substitution increases (decreases) the cross-country variation in relative skill efficiency, mechanically decreasing (increasing) the contribution of $\frac{Q_{H,c}}{Q_{L,c}}$ (whose estimate does not depend on the value of the elasticity). For the range of elasticities estimated in the literature, this contribution is between 5-16%.

[Figure III here]

5 Alternative Interpretations

In this section I discuss three potential concerns for my empirical approach. The first is that emigrants are typically not representative of the population of non-emigrants from the same country of origin. The second relates to the fact that workers’ skills might not be fully transferable across countries. The third is that migrants might be sorting into different labor markets within the United States.

5.1 Selection

Given that my approach relies on emigrant workers to estimate cross-country differences in the relative human capital endowment of high-skill labor, a natural concern is that emigrant workers are not randomly selected. In this section I discuss the possible consequences of selection and provide some evidence on its quantitative importance.
It is helpful to explicitly introduce some individual-level heterogeneity in the framework of section 4 to illustrate the main issues. Suppose that the human capital of individual $i$, of skill $S \in \{H, L\}$, having completed his or her education in country $a$ is $Q_{S,a}e^{\varepsilon_{S,a,i}}$, where $Q_{S,a}$ is a term common to all individuals of skill $S$ educated in $a$ and $\varepsilon_{S,a,i}$ is a mean-zero idiosyncratic factor capturing unobservable skills. If migrants are selected on unobservable skills, $E[\varepsilon_{S,a,i}|\text{migrant}] \neq 0$. The log relative human capital endowment I estimate out of US migrants would then read

$$\log Q_{H,a}^{US} - \log Q_{L,a}^{US} = \log Q_{H,a} - \log Q_{L,a} + E[\varepsilon_{H,a,i}|\text{migrant}] - E[\varepsilon_{L,a,i}|\text{migrant}]$$ (17)

which differs from the quantity of interest as long as $E[\varepsilon_{H,a,i}|\text{migrant}] \neq E[\varepsilon_{L,a,i}|\text{migrant}]$. Selection is therefore problematic to the extent that it takes place with different degrees across skill groups and countries of origin. In particular, a more positive degree of selection across high-skill immigrants from poor countries could in principle lead me to understate the magnitude of cross-country differences in the relative human capital of high-skill labor.

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 to 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

\[ Selection_{H,a} = e^{\mathbb{E}[\varepsilon_{H,a,i}|\text{migrant}]} \] \hspace{1cm} (18)

\[ Selection_{L,a} = e^{\mathbb{E}[\varepsilon_{L,a,i}|\text{migrant}]} \] \hspace{1cm} (19)

so that by taking

\[
\log \left( \frac{Selection_{H,a}}{Selection_{L,a}} \right) = \mathbb{E}[\varepsilon_{H,a,i}|\text{migrant}] - \mathbb{E}[\varepsilon_{L,a,i}|\text{migrant}]
\]

I obtain the country-specific factor I need to correct for the selection bias in (17). Figure IV 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 large gaps in relative human capital endowment between rich and poor countries. Moreover, across all GDP levels, the selection correction is an order of magnitude smaller compared to the gaps in the skill bias of technology displayed in Figure III, implying that such correction cannot significantly affect the conclusion that technology explains the lion share of the cross-country variation in relative skill efficiency.

[Figure IV here]

The second row of Table VI shows how the elasticities of \( \frac{Q_{H,c}}{Q_{L,c}} \) and \( \frac{A_{H,c}}{A_{L,c}} \) with respect to GDP per worker change after the selection correction (where each country is assigned the degree of differential selection corresponding to its GDP group).\(^{10}\) The relative human capital endowment of skilled labor contributes now only 1-4% to the association between relative skill efficiency and GDP per worker. This selection correction is quite crude, and might miss some heterogeneity in differential selection within GDP groups. However, these results do suggest that accounting for differential selection is unlikely to raise the cross-country variation

\(^{10}\)I do not apply any selection correction to the estimate of relative human capital endowment for the United States, since this is identified out of natives.
in the relative human capital endowment of high-skill labor.

### 5.2 Skill Loss and Skill Downgrading

Another concern is that human capital might be partially country-specific. Differences in language, culture and the institutional environment, or a poor fit between the educational curriculum and the needs of US employers could all imply a loss of productive skills upon migration. To the extent that this takes place differentially across skill levels, gaps in productive skills between high- and low-skill migrants will differ from those among non-migrants, even in absence of selection into migration.

To assess the importance of this, I re-estimate limiting the sample to migrants that are, according to observable characteristics, less likely to be affected by a lack of US-specific human capital. The third and fourth row of Table VI display results based on, respectively, migrants that have spent at least 10 years in the United States and migrants that report to speak English well.\(^{11}\) 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 marginally smaller compared to the baseline case (first row). This is consistent with the fact that poorer countries tend to be linguistically and culturally more distant from the United States, making it harder for immigrants from those countries to fully utilize their skills.\(^{12}\)

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 based on their skill endowments and the US prices of different kinds of labor services. For my purposes, this pattern can be problematic, since when comparing skill premia across nationalities as in (16) the technological and price terms would not necessarily cancel out.

\(^{11}\)The former involves dropping one country, Albania, for which all high-skill workers in the sample have less than 10 years in the United States.

\(^{12}\)Schoellman (2012) implements the same 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.
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.\textsuperscript{13} Figure V shows that the incidence of skill downgrading does vary somewhat across countries of origin: on average, about 40% immigrants from countries in the lowest quartile of the GDP distribution are subject to it, while the corresponding figure across US natives is 20%.

As a rough check on the implications of this for my results, I re-estimate skill premia excluding all skill-downgraded workers (either natives or immigrants) from the sample. The fifth row of Table VI shows that this results in slightly smaller cross-country differences in the inferred relative human capital of skilled labor, and a correspondingly larger role for the skill bias of technology.\textsuperscript{14} Of course, this exercise is plausibly plagued 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.

\section*{5.3 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 the United States, workers educated in different countries sort into labor markets that systematically differ along these dimensions.

\textsuperscript{13}The occupation classification available in the US Census includes 474 occupations. For workers holding multiple jobs, the recorded occupation is the most remunerative one.

\textsuperscript{14}This classification of high- and low-skill occupation implies that many (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 elasticity of $\frac{Q_H}{Q_L}$ with respect to GDP per worker is 0.057.
I consider two sources of within-country heterogeneity: sectors and regions. Consider first an environment with a sector-specific production technology,

\[ Y_{c,s} = A_{c,s} F (A_{K,c,s}K_{c,s}, A_{L,c,s}L_{c,s}, A_{H,c,s}H_{c,s}) \]

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

\[
\frac{w_{H,c,r}^a}{w_{L,c,s}^a} = \frac{A_{c,r} A_{H,c,r} Q_{H,c,r}^a F_H (A_{K,c,r}K_{c,r}, A_{L,c,r}L_{c,r}, A_{H,c,r}H_{c,r})}{A_{c,s} A_{L,c,s} Q_{L,c,s}^a F_L (A_{K,c,s}K_{c,s}, A_{L,c,s}L_{c,s}, A_{H,c,s}H_{c,s})} \tag{20}
\]

Equation (20) shows 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 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 nationality-specific skill premia controlling for sector and sector × skill fixed effects, and calculate the relative human capital endowments as in Section 4. Here, I make full use of the detailed sectoral classification available in the US Census, consisting of 226 different sectors. The third row of Table VI shows the resulting elasticities with respect to GDP per worker. Allowing for sectoral heterogeneity has a small negative effect on the cross-country variation of relative human capital. While, as documented in Section 3.3, 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 VI reports the results of the corresponding exercise by region. Here, 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 elasticity of relative human capital endowment is once again small and negative.

6 Discussion of Related Development Accounting Results

As mentioned in the Introduction, several papers have studied immigrants’ earnings for the purpose of development accounting. Compared to the present study, these papers have a different focus: in terms of my notation, they quantify the contribution of a combination of $Q_{H,c}$ and $Q_{L,c}$ (human capital per average worker) for the variation in $Y_c$, while my paper quantifies the contribution of $Q_{H,c}/Q_{L,c}$ (the relative human capital of high- and low-skill workers) for the variation in $(A_{H,c}Q_{H,c})/(A_{L,c}Q_{L,c})$ (the relative efficiency of high- and low-skill workers). Nevertheless, it is useful at this point to frame the results of my paper in the context of this literature.

The seminal paper in this line of work is Hendricks (2002). He studies average wage gaps between US natives and US immigrants, and since these gaps are relatively small he concludes that the cross-country variation in average human capital per worker is limited. This approach relies on a stronger selection assumption compared to the one discussed in Section 5.1: as long as migrants from poor countries are positively selected, their absolute wage gaps with respect to US natives will underestimate the human capital gaps for the average (non-migrant) worker.

Indeed, Hendricks and Schoellman (2018) show that this concern is well-founded, and that addressing it radically changes the conclusions for the importance of human capital. Their paper uses wage gains upon migration to quantify the cross-country variation in human capital per worker. The logic of their exercise is simple: the larger the gains upon migration are, the larger the role of factors other than human capital (such as technology and physical capital) in driving overall cross-country gaps in output are inferred to be. Since wage gains are substantially lower than overall output gaps, they conclude that human capital accounts for a large share of the cross-country variation in output.
Hendricks and Schoellman (2018) also report that, consistently with imperfect substitutability, wage gains are higher for less educated migrants (that are relatively scarce in the US). While average gains are only informative on average human capital gaps, the magnitude of these relative gains directly relates to the question of interest in this paper, i.e. the importance of the cross-country variation in relative human capital. Hendricks and Schoellman (2018) calibrate a model without differences in the skill bias of technology, and find that it can rationalise skill-specific wage gains only if the elasticity of substitution between low- and high-skill workers is substantially higher than what estimated in the literature (i.e. between 5 and 8, as opposed to between 1.3 and 2). Indeed, in ongoing work Hendricks and Schoellman (2019) show that the gains upon migration are consistent with models with large differences in the skill bias of technology, either exogenous or resulting from the endogenous response of firms to differences in the supply of skilled labor. These results resonate well with the findings of my paper.

In addition, it is interesting to relate my results to the ones in Schoellman (2012), who also builds on the insight that the variation in returns to education for home-educated immigrants is informative on the cross-country variation in educational quality. He estimates country-of-origin-specific Mincerian returns, and uses the results to discipline the calibration of country-specific human capital stocks, in a setup with perfect substitutability across skill types. The cross-country variation in the estimated human capital stocks is substantially larger compared to what one would find including schooling quantity as the only source of variation.

The calibration exercise is based on a model of endogenous schooling decisions. Through the lens of this model, the cross-country variation in schooling quantity is informative on the cross-country variation in the productivity gain associated to an additional year schooling (as in equilibrium the former increases the latter). The human capital stocks estimated by Schoellman (2012) incorporate this variation in schooling productivity, which, as acknowledged in the paper, might reflect both educational quality and the skill bias of technology. My results suggest that the latter might be the relatively more important factor.

All in all, the combination of these results paints a consistent picture of the cross-country variation in human capital and technology. Human capital differences appear to be large and,
for the most part, uniform across different levels of educational attainment (that is, both $Q_{H,c}$ and $Q_{L,c}$ are significantly larger in rich countries, while differences in $Q_{H,c}/Q_{L,c}$ are small).

This pattern puts restrictions on the set of likely sources of cross-country human capital gaps, with early childhood education, parental influences and out-of-school human capital accumulation being natural candidates. At the same time, rich countries adopt technologies that make skilled labor relatively more productive (that is, $A_{H,c}/A_{L,c}$ is significantly larger in rich countries), and this variation in the technology mix might also contribute to cross-country differences in economic performance.

I conclude this section by discussing an observation commonly made in the literature, which might be read as an objection to the practical importance of the distinction between human capital and technology in this context. Some authors point out that the skill bias of technology is an endogenous object that depends directly on the relative quality and quantity of skilled labor; that is, $A_{H,c}/A_{L,c}$ is itself a function of $Q_{H,c}/Q_{L,c}$ (and $\tilde{H}/\tilde{L}$). This view is supported by several pieces of empirical evidence showing that technology adoption does respond to factor abundance (see for example Caselli and Wilson, 2004; Beaudry et al., 2010; Lewis, 2011). Of course this evidence does not imply that the relative supply of high-skill labor is the only factor influencing the adoption of skill-biased technology; indeed, several others (such as institutional quality, credit availability, market structure) are likely to play a role. Quantifying the “elasticity” of $A_{H,c}/A_{L,c}$ with respect to $Q_{H,c}/Q_{L,c}$ or $\tilde{H}/\tilde{L}$ is an interesting open issue for further research. Even if a large part of the variation in $A_{H,c}/A_{L,c}$ is in fact driven by skill availability, understanding to what extent the impact of human capital on relative skill efficiency is direct, as opposed to occurring through the adoption of complementary technologies, is important. First, the result that $A_{H,c}/A_{L,c}$ varies more than $Q_{H,c}/Q_{L,c}$ points to the importance of identifying and removing frictions on the margin of skill-biased technology adoption, as those frictions could slow down significantly the catch up process in

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15 See Rossi (2018) for a review of the existing work on these topics.
16 Caselli and Coleman (2006) develop a theory where countries adopt different mixes of high- and low-skill-augmenting technologies depending on the relative supply of high-skill labor. This model is used for a development accounting exercise in Hendricks and Schoellman (2019).
17 My empirical strategy is not directly informative on this issue: migrants’ wages are useful to detect whether $A_{H,c}/A_{L,c}$ is higher in rich countries, but not to understand why this is the case.
labor productivity. Second, this result suggests that the bundles of technologies employed in rich and poor countries are very different, which supports the view that the innovation taking place in rich countries might be “inappropriate” for poor countries (Acemoglu and Zilibotti, 2001).

7 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 various 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. Cross-nationality patterns in the skill premium among US immigrants suggest 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 technological 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 technology. The existing literature mostly emphasizes skill availability at the country level as a factor driving skill-biased technological adoption. Quantifying this and other alternative mechanisms would provide useful insights on the cross-country variation in the structure of production and its implications for economic development. Along the lines of this paper, one likely source of further progress in this direction 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 fact that the relative human capital endowment of high- and low-skill workers does not vary dramatically between rich and poor countries does not imply that human capital plays a small role for economic development. In fact, recent evidence based on migrants’ wages suggests the opposite, and is consistent with the view that the human capital embodied in both high- and low-skill workers is higher in rich countries. The
fact that cross-country differences in human capital are relatively uniform across skill levels puts important restrictions on theories of human capital accumulation and economic development, calling for a stronger emphasis on investments happening outside of the formal school system. Identifying and quantifying these forms of human capital accumulation represent exciting avenues for future research.
References


## Tables

### Table I: Skill Premium, Supply and Efficiency across Countries

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**Elasticity wrt GDP p.w.**

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<th>-0.138</th>
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<td>(0.402)</td>
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**Elasticity wrt $\tilde{H}/\tilde{L}$**

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<td>(0.168)</td>
<td>(0.153)</td>
<td>(0.110)</td>
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**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 two rows show the coefficient of a regression of the log of each variable on log GDP per capita and log relative skill supply (standard errors in parentheses).
Table II: Skill Premium, Supply and Efficiency across Countries - Controls

<table>
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<th>Country</th>
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<th>$\tilde{H}/\tilde{L}$</th>
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Elasticity wrt GDP p.w.:

-0.024 0.796*** 1.520***

Elasticity wrt $\tilde{H}/\tilde{L}$:

-0.119 1 1.644***

Notes: The Table shows the skill premium, relative skill supply and efficiency for the specification including controls for gender and potential experience. Relative skill efficiency is normalised such that it takes value 1 for the United States. The last two rows show the coefficient of a regression of the log of each variable on log GDP per capita and log relative skill supply (standard errors in parentheses).
Table III: Relative Skill Efficiency: the Role of Self-Employment

<table>
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Notes: The Table shows the skill premium, relative skill supply and efficiency across the countries in the sample. Relative skill efficiency is normalised such that it takes value 1 for the United States. Wage Workers Only refers to the baseline specification, while Wage Workers and Self-Employed refers to results when the self-employed are included for the estimation of the skill premium.
### Table IV: Relative Skill Efficiency - The Role of Sectorial Composition

\[
\frac{(A_H Q_H)}{(A_L Q_L)}
\]

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<td>0.133</td>
<td>0.301</td>
<td>0.317</td>
<td>2.654</td>
<td>1</td>
</tr>
</tbody>
</table>

Elasticity wrt GDP p.w.  
\[1.408^{***} \quad 1.718^{***} \quad 0.952^{***} \quad 0.992^{**} \quad 0.850^{**} \quad 1.236^{***}\]
\[(0.394) \quad (0.466) \quad (0.266) \quad (0.359) \quad (0.360) \quad (0.385)\]

**Notes:** The Table shows the aggregate and sector-specific relative skill efficiency across the countries in the sample, as defined in the text. Aggregate relative skill efficiency is normalised such that it takes value 1 for the United States. *Counterfactual* refers to the counterfactual relative skill efficiency obtained when assigning to each country the US sectorial shares by education, as explained in the text. The last row shows the coefficient of a regression of the log of each variable and log GDP per capita (standard errors in parentheses).
Table V: Relative Skill Efficiency - Robustness

\[ \frac{(A_H Q_H)}{(A_L Q_L)} \]

<table>
<thead>
<tr>
<th>Country</th>
<th>Baseline</th>
<th>Different Elasticities</th>
<th>Different High-Skill Thresholds</th>
<th>Capital-Skill Complementarity</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( \sigma = 1.3 )</td>
<td>( \sigma = 2 )</td>
<td>Upper Secondary</td>
<td>Tertiary</td>
</tr>
<tr>
<td>India</td>
<td>0.041</td>
<td>0.004</td>
<td>0.224</td>
<td>0.004</td>
</tr>
<tr>
<td>Indonesia</td>
<td>0.003</td>
<td>0.7 \times 10^{-4}</td>
<td>0.059</td>
<td>0.001</td>
</tr>
<tr>
<td>Jamaica</td>
<td>0.010</td>
<td>0.3 \times 10^{-3}</td>
<td>0.130</td>
<td>0.009</td>
</tr>
<tr>
<td>Brazil</td>
<td>0.087</td>
<td>0.011</td>
<td>0.405</td>
<td>0.010</td>
</tr>
<tr>
<td>Venezuela</td>
<td>0.089</td>
<td>0.014</td>
<td>0.351</td>
<td>0.009</td>
</tr>
<tr>
<td>Uruguay</td>
<td>0.126</td>
<td>0.028</td>
<td>0.394</td>
<td>0.007</td>
</tr>
<tr>
<td>Panama</td>
<td>0.099</td>
<td>0.018</td>
<td>0.353</td>
<td>0.010</td>
</tr>
<tr>
<td>Mexico</td>
<td>0.048</td>
<td>0.005</td>
<td>0.241</td>
<td>0.004</td>
</tr>
<tr>
<td>Trinidad and Tobago</td>
<td>0.018</td>
<td>0.001</td>
<td>0.166</td>
<td>0.028</td>
</tr>
<tr>
<td>Israel</td>
<td>0.129</td>
<td>0.036</td>
<td>0.339</td>
<td>0.047</td>
</tr>
<tr>
<td>Canada</td>
<td>0.711</td>
<td>0.638</td>
<td>0.772</td>
<td>0.099</td>
</tr>
<tr>
<td>United States</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

Elasticity wrt GDP p.w.  

\[
\begin{align*}
\text{Elasticity} & \quad 1.408^{***} & 2.439^{***} & 0.635^{***} & 1.682^{***} & 0.976 & 0.727^{**} \\
\text{(Standard Error)} & \quad (0.394) & (0.667) & (0.194) & (0.361) & (0.903) & (0.292) 
\end{align*}
\]

Notes: The Table shows the relative skill efficiency across the countries in the micro-data sample. The first column reports the baseline results, while other columns correspond to different robustness checks, as indicated in the column headings. For all columns, relative skill efficiency is normalised such that it takes value 1 for the United States. The last row shows the coefficient of a regression of the log of each variable and log GDP per capita (standard errors in parentheses).
### Table VI: Relative Technology and Human Capital across Countries

<table>
<thead>
<tr>
<th>Elasticity wrt GDP p.w.</th>
<th>( \sigma = 1.5 )</th>
<th>( \sigma = 1.3 )</th>
<th>( \sigma = 2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( q_H/q_L )</td>
<td>0.082***</td>
<td>1.017***</td>
<td>0.426***</td>
</tr>
<tr>
<td>( q_H/q_L )</td>
<td>(0.016)</td>
<td>(0.193)</td>
<td>(0.102)</td>
</tr>
<tr>
<td>( A_H/A_L )</td>
<td>0.935***</td>
<td>1.694***</td>
<td>0.508***</td>
</tr>
<tr>
<td>( A_H/A_L )</td>
<td>(0.198)</td>
<td>(0.322)</td>
<td>(0.097)</td>
</tr>
<tr>
<td>( A_Hq_H/A_Lq_L )</td>
<td>1.017***</td>
<td>1.694***</td>
<td>0.508***</td>
</tr>
<tr>
<td>( A_Hq_H/A_Lq_L )</td>
<td>(0.193)</td>
<td>(0.322)</td>
<td>(0.097)</td>
</tr>
<tr>
<td>( A_H/A_L )</td>
<td>1.613***</td>
<td>0.426***</td>
<td>0.508***</td>
</tr>
<tr>
<td>( A_H/A_L )</td>
<td>(0.326)</td>
<td>(0.102)</td>
<td>(0.097)</td>
</tr>
<tr>
<td>( A_Hq_H/A_Lq_L )</td>
<td>1.694***</td>
<td>0.508***</td>
<td>0.508***</td>
</tr>
<tr>
<td>( A_Hq_H/A_Lq_L )</td>
<td>(0.322)</td>
<td>(0.102)</td>
<td>(0.097)</td>
</tr>
</tbody>
</table>

Notes: The Table shows the elasticity (standard errors in parentheses) with respect to GDP per capita of the relative human capital endowment of skilled labor, technology skill bias and relative skill efficiency, across different specifications. The elasticities are estimated in the broad sample (65 countries); the estimates for 10+ Years in US exclude Albania as explained in footnote 11. 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.
Figures

Figure I: Relative Skill Efficiency across Countries

Notes: The figure plots on a log scale relative skill efficiency and GDP per worker for the 12 countries in the micro-data sample. Both variables are normalized so that they take value 1 for the United States. The solid line represents the best exponential 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: Relative Human Capital and Skill Bias of Technology across Countries

Notes: The left graph plots the log relative human capital endowment of high-skill labor against log GDP per capita. The right graph plots the log skill bias of technology against log GDP per capita. Both the relative human capital endowment 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 IV: 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 V: 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.