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

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Abstract

This paper studies how the relative productivity of skilled and unskilled 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, in spite of large differences in the relative skill supply. This pattern is consistent with the view that the relative productivity of skilled workers is higher 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 technology and unobserved human capital as drivers of these patterns. I find that human capital quality plays a minor role in explaining cross-country differences in relative skill efficiency.

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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, thanks both to improved measurements of production inputs (Schoellman, 2012; Lagakos et al., 2016) and richer characterizations of the production technology (Jones, 2014; Caselli, 2016).

An emerging view in this line of research is that the relative efficiency of skilled and unskilled 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, in spite of large gaps in enrollment rates and educational achievements. This suggests that high-skilled workers are much more productive in rich (and skill-abundant) countries, attenuating the downward pressure on the skill premium stemming from their high supply. Cross-country gaps in the productivity of unskilled labor are instead moderate in size.

Different interpretations have been proposed to explain these patterns. One possibility, first advanced by Caselli and Coleman (2006) and Caselli (2016), is that technological differences across countries are factor-biased, and firms in rich countries adopt technologies more suitable for skilled workers. A natural alternative is that the human capital gap between high- and low-skill workers is larger in rich countries, because of differences in educational quality, training or workers' intrinsic characteristics (Jones, 2014; Malmberg, 2017). In a cross-country setting, distinguishing between the two 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 intepretation of cross-country differences in relative skill efficiency. Using both aggregate and micro-level data, I confirm that gaps in the relative productivity of skilled and unskilled labor are large and not driven by the limited comparability or reliability of some of the sources used in previous studies. 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 main data contribution of the paper consists in the construction of highly comparable estimates for the skill premium across countries. The lack of such information has represented a major drag on the existing literature, which has relied either on imputations based on related quantities, or on the use of sources not fully consistent with the underlying modelling strategy. To improve on this, I use micro-data from IPUMS International on 12 countries at different stages of development, ranging from the United States to India.[1] I estimate the skill premium using the same specifications and similar sample restrictions for all countries. While the magnitude of some of the estimates is quite different from existing sources, I confirm the finding that the skill premium varies little across countries.

Through the lens of a simple production function setting, I back out the implied relative efficiency of skilled labor for each country, using both micro-data from IPUMS and more traditional sources to estimate the relevant parameters. I embed in this framework differences in both relative human capital and technology bias, and show that the estimated relative skill efficiency is a composite of the two. I confirm that relative skill efficiency varies substantially across countries. Cross-country gaps in relative skill efficiency are of a similar magnitude of cross-country gaps in GDP per capita.

I then study the sources of these gaps. 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 vary in their productivity, and differently so depending on their level of educational attainment. Gaps in the relative productivity of skilled labor might reflect differences in educational quality, as emphasized in Schoellman (2012), or differential of sorting into higher education across countries. I then show that comparing the within-group skill premia across immigrants' countries of origin provides a way to isolate cross-country differences in relative human capital quality, keeping constant the local technological environment and other institutional characteristics.

I find that the cross-country variation in relative skill quality is of limited magnitude. While the productivity gap between skilled and unskilled workers is higher in the United States compared to most countries, the differences are much smaller than what would be expected in a world where human capital quality explained the cross-country gaps in skill efficiency. Indeed, I conclude that differences in the skill bias of technology accounts for more than 90% of the cross-country variance in skill efficiency. While in principle patterns of differential selection into migration and occupational downgrading as a function of skills and country of origin might contribute to shape these results, I argue that this concern is unlikely to majorly affect the basic conclusion of the paper.

My work fits in the literature on cross-country differences in the structure of production.

[1] Caselli and Ciccone (2013) use the same source to compute a number of wage statistics for different countries, but they do not relate them directly to cross-country differences in the relative efficiency of skilled labor.

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 an improved measurement of skill premia and the development of a methodology to discriminate between relative skill quality and technology bias as sources of differences in skill efficiency. This distinction mirrors, on a cross-country dimension, a related debate on the relative roles of technology, human capital and sorting 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; Schoellman and Hendricks, 2017). In particular, Schoellman (2012) uses estimated Mincerian returns to schooling across immigrants' nationalities to quantify the role of educational quality for development accounting. While his focus is the aggregate human capital stock (in a model with perfect substitutability across skill levels), the main object of interest of my analysis is the relative quality of high-skill and low-skill workers. Immigrants from rich countries have higher returns both within and between skill levels, but the variation in returns between skill groups (which drive my estimates of relative skill quality) is more limited.

The paper is structured as follows. Section 2 describes the micro 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 concerns and alternative interpretations for the results. Finally, Section 6 concludes by discussing some implications and possibilities for future work.

2 Data

The main ingredients for the computation of skill-specific efficiency gaps are measures of the relative price and quantity of skilled labor. To the best of my knowledge, no existing dataset provides a measure of the skill premium which is comparable across countries, nationally representative and consistent with the skill categorization used in this paper and the rest of the literature. Sources like ILOSTAT, compiled by the International Labor Organization, allow to contruct, for a limited number of countries, wage gaps between workers in different occupations or economic activities (as opposed to different educational attainments). This is problematic, as occupations and their skill content are difficult to compare across countries at different stages of development. Moreover, these data do not allow to condition in a comparable way on hours worked, employment status, experience, gender and other observable characteristics. Relying on cross-country meta-collections of Mincerian coefficients (such as Psacharopoulos and Patrinos (2004), Banerjee and Duflo (2005) and Caselli et al. (2016)) is also not fully satosfactory, since the human capital aggregators with imperfect substitutability typically are not consistent with log-linear returns to schooling, and given that the estimates in these collections come mostly from studies with not nationally representative samples, different controls and specifications.

For what concerns the quantity of skilled labor, existing sources for cross-country comparisons of educational attainment, such as Barro and Lee (2013), focus on the education level of the working age population, with no differentiation based on employment status or hours worked.[2] Moreover, the aggregation of heterogeneous types of human capital typically relies on relative wages, and in absence of country-specific data on those the common practice is to apply estimates for the United States to all countries (Caselli, 2016).

To improve on these and other dimensions, I use a collection of Census data from several different countries, harmonized by IPUMS and IPUMS International. I consider all countries where rich enough information on wages or earnings, education, labor market status, gender, experience and sector of employment are available. This leaves me with 12 countries in 2000 or a close year, including (according to the World Bank classification) high-income (United States, Canada, Israel, Trininidad 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 (2017) and Lagakos et al. (2017).

I construct hourly wages from available information on annual or weekly wages and hours worked. I classify workers into five levels of educational attainment: primary or less, some secondary, secondary completed, some tertiary and tertiary completed. I define (potential) experience as the difference between current age and age at the end of education, and I consider nine groups based on 5-year intervals (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). I use data from the World Bank's World Development Indicators to infer the country-specific duration of each education stage.[3]

A possible concern for studying skill premia in a comparative perspective is that the share of wage employment varies considerably across countries, and self-employment is prevalent

[2]Moreover, for the youngest generations Barro and Lee (2013) provide an estimate of the *final* level of education, while the appropriate object for the purpose of evaluating the current productive role of human capital would be the level of education of workers currently employed.

[3]There are some exceptions in terms of data coverage. India, Panama and Uruguay provide no information on labor supply. For Brazil, Mexico and Venezuela I use total earnings as wages are unavailable.

in poor countries and in agriculture in particular. For a few countries in my sample, Canada, Panama, Trinidad and Tobago and the United States, the Census I use includes information on self-employment income, which, under some caveats discussed below, can be used to infer to what extent measures of returns to skills based on relative wages are incomplete.

3 Measuring Relative Skill Efficiency

In this section I document how the relative efficiency of skilled labor varies across countries. I introduce a simple framework, discuss how I bring it to the data and summarize the main patterns.

3.1 Framework

Throughout the paper, I consider variants of the generic aggregate production technology for each country c

$$Y_c = A_c F(A_{Kc}K_c, A_{1c}X_{1c}, \ldots, A_{Nc}X_{Nc})$$

where K_c is physical capital and $X_{1c}, \ldots, X_{Nc}$ are different types of labor services. In the empirical applications that follow, different types of workers correspond to different combinations of educational attainment, gender and experience. The production function involves several technological paramenters, potentially varying across countries: A_c is total factor productivity, while $A_{Kc}, A_{1c}, \ldots, A_{Nc}$ are factor biased technological terms, augmenting physical capital and labor services. To simplify the notation, in what follows I omit the subscript c where this does not generate confusion.

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

$$X_{nc} = Q_{nc}\tilde{X}_{nc}$$

where $\tilde{X}_{Nc}$ represents the quantity of workers of type n employed in country c, while Q_{nc} captures their quality, or the amount of labor services provided by a given worker. While $A_{1c}, \ldots, A_{Nc}$ proxy for factors external to individuals, such as the available technologies and the features of the working environment, I think of $Q_{1c}, \ldots, Q_{Nc}$ as capturing workers' embodied human capital, which is possibly the result of both accumulated knowledge and innate characteristics.

Workers of type n in country c provide therefore $A_{nc}Q_{nc}$ efficiency units. Workers' efficiency is a product 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

$$\frac{w_{Hc}}{w_{Lc}} = \frac{A_{Hc}Q_{Hc}}{A_{Lc}Q_{Lc}} \frac{F_H(A_{Kc}K_c, A_{1c}X_{1c}, \ldots, A_{Nc}X_{Nc})}{F_L(A_{Kc}K_c, A_{1c}X_{1c}, \ldots, A_{Nc}X_{Nc})} \tag{1}$$

where $\frac{A_{Hc}Q_{Hc}}{A_{Lc}Q_{Lc}}$ is the relative efficiency of workers of type H and L and $\frac{F_H}{F_L}$ is the relative price of an efficiency units supplied by the two types.

Equation (1) is the relationship I bring to the data to measure the relative efficiency of skilled and unskilled labor. To be able to do that, I need to (i) identify skilled and unskilled workers, (ii) measure the corresponding skill wage ratio and (iii) back out the relative price of an efficiency unit. I start from a baseline set of assumptions in the next section, and consider several alternatives in the following ones.

3.2 Baseline Specification

For my baseline specification, I follow most of the literature in considering a CES human capital aggregator of two types of workers, skilled and unskilled, with physical capital and human capital assumed to be separable. More specifically,

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

where the human capital aggregator G is given by

$$G\left(A_{Lc}L_c, A_{Hc}H_c\right) = \left[(A_{Hc}H_c)^\rho + (A_{Lc}L_c)^\rho\right]^{\frac{1}{\rho}}$$

Here, H_c and L_c denote high-skilled and low-skilled labor services, and $\frac{1}{1-\rho}$ is the elasticity of substitution between the two. High- and low-skill labor services are given by the product of the number of workers in each category and their human capital

$$H_c = Q_{Hc}\tilde{H}_c \tag{2}$$

$$L_c = Q_{Lc}\tilde{L}_c \tag{3}$$

The skill premium, i.e. the relative wage of skilled and unskilled workers, is

$$\frac{w_{Hc}}{w_{Lc}} = \left(\frac{A_{Hc}Q_{Hc}}{A_{Lc}Q_{Lc}}\right)^\rho \left(\frac{\tilde{H}_c}{\tilde{L}_c}\right)^{\rho-1} \tag{4}$$

I refer to $\frac{A_{Hc}Q_{Hc}}{A_{Lc}Q_{Lc}}$ as the relative "efficiency" of skilled and unskilled workers. If $\rho >$

0, which is 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, $\frac{A_H}{A_L}$, and differences in the relative quality of skilled labor, $\frac{Q_H}{Q_L}$. 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.

When bringing this framework to the data, key choices to make is how to assign workers to the high- and low-skill categories, and how to model the heterogeneity within skill groups. Following most of the literature, I adopt a criterion based on workers' level of educational attainment. For my baseline, I consider skilled all workers with some college education, while individuals with at most an high-school degree are unskilled. This split is in the middle range of what the literature has considered.[4] Moreover, as discussed in Section 3.3.1, this turns out to be a conservative choice. For the elasticity of substitution, I rely on Ciccone and Peri (2005), who provide a credibly identified estimate of 1.5 on US data (which implies a value for ρ of 1/3).

Within these broad skill categories, workers are perfect subsitutes and supply different efficiency units depending on their educational attainment (indexed by j), gender (indexed by g) and experience (indexed by exp). For educational attainment, I split the unskilled in three groups (primary or less, some secondary, secondary completed) and the skilled in two groups (some tertiary, tertiary completed).[5] I define (potential) experience as the difference between current age and age at the end of education, and I consider nine groups based on 5-year intervals (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). The aggregators $\tilde{H}$ ($\tilde{L}$) are expressed in terms of equivalents of college (some secondary) educated, male and less than 5 years experienced workers, which I refer

[4] The earlier part of the literature, and Caselli and Coleman (2006) in particular, used a wider definition of skilled labor as their benchmark. Given that I am looking at a more recent period and, especially, a sample of richer countries, it seems appropriate to start from a more restrictive definition. See 3.3.1 for some possible alternatives.

[5] While the cross-country data in Barro and Lee (2013) allows to distinguish also between workers with no education, some primary and primary completed, the Censuses for a few countries do not fully distinguish between these subcategories. Moreover, sample sizes are small at these levels of educational attainment, especially by immigrants' countries of origin.

to "baseline" skilled (unskilled) workers. They take the form[6]

$$\tilde{H} = \sum_{j \in H} \sum_{g} \sum_{exp} \frac{Q_{j,g,exp}}{Q_{college,male,0to4}} \tilde{X}_{j,g,exp} \tag{5}$$

$$\tilde{L} = \sum_{j \in L} \sum_{g} \sum_{exp} \frac{Q_{j,g,exp}}{Q_{some\ sec,male,0to4}} \tilde{X}_{j,g,exp} \tag{6}$$

where $\tilde{X}_{j,g,exp}$ is the number of workers belonging to the (j, g, exp) group.[7] Given that sample sizes are often small at the (j, g, exp) level, I simplify the estimation by assuming that the log gaps across groups in terms of efficiency units are not interactive in education, gender, experience, that is

$$Q_{j,g,exp} = e^{\beta_j} e^{\lambda_g} e^{\mu_{exp}} \quad \forall \quad j, g, exp$$

I then use the assumption of perfectly competitive labor markets to estimate β_j, λ_g and μ_{exp}. In particular, perfect competition implies that the average log wage of a worker of skill $S \in \{H, L\}$, with educational attainment j, gender g and experience exp is:

$$\log w_{S(j,g,exp)} = \alpha + \gamma_S + \beta_j + \lambda_g + \mu_{exp} \tag{7}$$

where α is a constant and $\gamma_S = \log\left(A_S Q_S\right)^{\rho} (\tilde{S})^{\rho-1}$. The parameters β_j, λ_g and μ_{exp} can be therefore identified from a regression of log wages on skill group, educational attainment, gender and experience fixed effects, where I normalize $\beta_{college} = \beta_{some\ sec} = \lambda_{male} = \mu_{0to4} = 0$.[8] Moreover, the coefficient on γ_H (with low-skilled workers being the omitted cateogory) identifies the log skill premium, i.e. the log wage differential between baseline skilled and unskilled workers. I run this specification using data from each Census, focusing on a sample of native individuals between 15 and 64 years old with a relatively high degree of labor market attachment.[9]

[6]With a slight abuse of notation, I denote by $j \in H$ ($j \in L$) the educational attainment levels assumed to be high- (low-) skill.

[7]The assumption that within skill groups differences in efficiency units are driven by human capital as opposed to technology is not crucial. Indeed, one can rewrite an equivalent formulation where both human capital and technology are specific to each (j, g, exp) group. In that setting, the relative technology bias I back out in this paper is the one between workers with college and some secondary education.

[8]Individual-level heterogeneity, resulting in an error in term in 7, can be easily added to the model; see Section 5.1. Of course, this specification might fail to capture causal effects, as several relevant unobservables are likely to be correlated with the regressors. The literature on returns to schooling, however, finds that OLS and IV estimates are often close in magnitude (Card, 2001).

[9]I restrict the sample to individuals that report working for wages, for at least 30 weeks and 30 hours per week in the previous year. In two countries, Israel and Jamaica, the information in IPUMS does not allow to identify individuals with some (not complete) secondary education, making it impossible to estimate the return to this level of educational attainment. As in Barro and Lee (2013)'s data the share of individuals with incomplete secondary education is positive, I impute their return interpolating the returns to primary and

With the estimates of β_j, λ_g and μ_{exp} at hand I can compute $\tilde{H}$ and $\tilde{L}$ for all countries. Combined the estimated skill premium, this allows me to back out $\frac{A_H Q_H}{A_L Q_L}$ from (4). Table I displays the skill premia, skill relative supplies and relative efficiencies for all countries.

The skill premium is on average lower in countries with higher supply of skilled labor, but the range of its variation is relatively modest. Coupled with the large gaps in relative human capital displayed in the second column, this implies large cross-country differences in the relative efficiency of skilled labor (third column). The magnitudes are striking: a 1% increase in GDP per capita is accompanied by a 1.11% increase in the relative skill efficiency. The gap with respect to the US ranges from a factor of 1.5 for Canada to a factor of 50 for the poorest countries in the sample. Figure I shows that the relative efficiency skilled labor is strongly positively related to its relative supply.

The result is driven by the fact that the relationship between the skill premium and the relative supply of skilled workers is not steep enough, so that a high efficiency of skilled labor in skill-abundant countries is needed to fit the data. Figure II illustrates this point by plotting the log skill premium against the log relative supply. The dashed line has a slope of $\rho - 1 = -0.67$, which is the predicted slope of this relationship in a world where $\log \frac{A_H Q_H}{A_L Q_L}$ was constant across countries (or, more generally, uncorrelated with $\log \frac{\tilde{H}}{\tilde{L}}$). The best linear fit (solid line) has instead an estimated slope of -0.28, with a standard error of 0.03. This implies that $\log \frac{A_H Q_H}{A_L Q_L}$ must increase with $\log \frac{\tilde{H}}{\tilde{L}}$. To give an example, in a world where all countries had the US level of efficiency bias, the model would predict for Indonesia a wage ratio of 26, while the actual ratio is 2.12.

The last three columns of Table I illustrate the impact of the improved measurement of wages and human capital I am able to provide in this paper. Column 4 shows relative skill efficiency without considering the variation in hours worked. Consistently with the evidence in Bick et al. (2016), all workers tend to work less hours in rich countries compared to poor countries; however, relatively to the unskilled, skilled workers work more hours in rich countries. This implies that by ignoring hours worked one understates the cross-country gap in relative skill supply; as a consequence of this, for a given skill premium the inferred relative efficiency is relatively higher in poor countries. This is even more true when the employment status is ignored altogether, i.e. when the human capital stocks are constructed including the inactive and the unemployed (column 5). Column 6 considers a specification where, along the lines of Caselli and Coleman (2006), skill premia and human capital stocks are constructed using estimates of country-specific Mincerian returns (taken from Caselli et al. (2016)). The elasticity of relative skill efficiency with respect to GDP per capita is now up to 1.5, with the relationship being much noisier. This reflects the fact that skill premia

secondary education, using the returns to primary, some secondary and secondary education in the other 10 countries to construct the weights.

inferred from Mincerian returns understate the cross-country variation in actual skill premia.

Overall, the takeaway message of my measurement refinements is that both relative human capital stocks and skill premia vary more across countries than previosly thought. The second effect is stronger than the first, therefore reducing by about one quarter the slope of the relationship between relative skill efficiency and economic development. This still leaves large cross-country gaps in the relative efficiency units provided by skilled labor.

3.3 Alternative Human Capital Aggregators

In this section I consider whether the result that relative skill efficiency is higher in rich countries depends on the specific way different types of human capital enter in the production function. I focus on two variations to the baseline framework in Section 3.2: alternative thresholds to classifiy skilled and unskilled workers and the introduction of a middle-skill group.

3.3.1 Alternative Skill Thresholds

The choice of which workers belong to the skilled and unskilled groups is somewhat arbitrary. While part of macro-development literature has considered secondary educated workers high-skilled (Caselli and Coleman, 2006), in labor economics the skilled-unskilled contrapposition is often cast in terms of high-school and college graduates. The second and third columns of Table II show the results for two alternative skill thresholds: secondary completed and tertiary completed. Since rich countries have on average more high-school graduates than poor countries, considering them high-skilled exacerbates the cross-country variation in the relative supply of skilled labor, therefore leading to a larger dispersion in inferred relative skill efficiency for a given skill premium (column 2). Instead, including only college graduates in the high-skill group (as opposed to college graduates and workers with some college education, like an associate degree for the US) does not impact much the slope of the relationship between skill efficiency and GDP per capita, though it adds considerable noise to it (column 3).

3.3.2 Imperfect Substitutability across Three Skill Groups

A natural generalization of the analysis in Section 3.2 is to consider more than two skill groups as imperfect subsitutes. Here, a word of caution is in order. The micro evidence on the elasticity of substitution across different levels of skills is limited, and once we move away from the skill split considered in Ciccone and Peri (2005), there is little or no guidance on how to calibrate the parameters of the production function.

Nevertheless, a natural starting point is to assume that the elasticity of substitution estimated by Ciccone and Peri (2005) applies to more than two groups. I consider here the human capital aggregator

$$G\left(A_{Lc}L_c, A_{Mc}M_c, A_{Hc}H_c\right) = \left[\left(A_{Hc}H_c\right)^{\rho} + \left(A_{Mc}M_c\right)^{\rho} + \left(A_{Lc}L_c\right)^{\rho}\right]^{\frac{1}{\rho}}$$

where $M_c = Q_{Mc}\tilde{M}_c$ represents labor services for middle-skill labor, A_{Mc} is the corresponding factor-biased technology term and everything else is defined as before. I define middle-skill workers as high-school graduates, and high-skill as workers with some tertiary education. The computation of skill premia and human capital stocks follows the same steps as in Section 3.2, with $\tilde{H}_c$ and $\tilde{L}_c$ still expressed in terms of college educated and high-school dropouts equivalents. I focus on the relative efficiency of high-skill and low-skill labor, backed out from

$$\frac{w_{Hc}}{w_{Lc}} = \left(\frac{A_{Hc}Q_{Hc}}{A_{Lc}Q_{Lc}}\right)^{\rho}\left(\frac{\tilde{H}_c}{\tilde{L}_c}\right)^{\rho-1}$$

Column 4 of Table II shows the results. Compared to the baseline exercise reported in the first columns, the key difference is that the low-skill human capital stock does not include workers with at least some tertiary education. Given that rich countries have more high-school educated workers than poor countries, the relative skill supply gaps across countries are a bit larger when high-school educated workers are not part of the high-skill group, resulting in larger relative skill efficiency gaps for a given skill premium. However, the impact of this modification is generally limited, and the main conclusion remains unaffected.

3.4 The Role of Self-Employment

As it is well known, self-employment is much prevalent in poor countries compared to rich countries. While the self-employed do enter in the computations of the human capital stocks described above, by construction they are not part of the specifications to estimate skill premia. This might be problematic to the extent that the efficiency unit gap between high-skilled and low-skilled individuals is different for self-employed and wage workers.

A few countries in my sample, namely Canada, Panama, Trinidad and Tobago and the United States, the Census I use includes information on self-employment income. As discussed in Herrendorf and Schoellman (2017), 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, among the countries for which self-employed income is avaiable, the cross-country variation in skill premia is a 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 very large gaps persist nevertheless.

3.5 Skill-Efficiency across Sectors

An advantage of the data I use in this paper is that they allow to study the variation of relative skill efficiency at a more disaggregated level. If one is willing to postulate sectorial production functions, sector-specific relative skill efficiencies can be backed out using sector-specific skill premia and human capital stocks. While a full examination of the determinants of the cross-sector dispersions in the relative efficiency of skilled labor is beyond the scope of this paper, in this section I propose a preliminary exploration of the possible implications of sectorial heterogeneity for the inferred aggregate relative skill efficiency.

Suppose that the human capital aggregator in sector s and country c is

$$G\left(A_{Lsc}L_{sc}, A_{Hsc}H_{sc}\right) = \left[\left(A_{Hsc}H_{sc}\right)^{\rho} + \left(A_{Lsc}L_{sc}\right)^{\rho}\right]^{\frac{1}{\rho}}$$

with the sector-specific skill premium given by

$$\frac{w_{Hsc}}{w_{Lsc}} = \left(\frac{A_{Hsc}Q_{Hsc}}{A_{Lsc}Q_{Lsc}}\right)^{\rho}\left(\frac{\tilde{H}_{sc}}{\tilde{L}_{sc}}\right)^{\rho-1}$$

The aggregate skill premium, i.e. the ratio of average high- and low-skill wages, can be written as

$$\frac{w_{Hc}}{w_{Lc}} = \left[\left(\sum_{s}\frac{\tilde{L}_{c,s}}{\tilde{L}_{c}}\left(\frac{w_{Hc}/w_{Lc}}{w_{Hc,s}/w_{Lc,s}}\right)^{\frac{1}{1-\rho}}\left(\frac{A_{Hc,s}Q_{Hc,s}}{A_{Lc,s}Q_{Lc,s}}\right)^{\frac{\rho}{1-\rho}}\right)^{\frac{1-\rho}{\rho}}\right]^{\rho}\left(\frac{\tilde{H}_{c}}{\tilde{L}_{c}}\right)^{\rho-1}$$

where $\tilde{H}_c = \sum_s \tilde{H}_{sc}$ and $\tilde{L}_c = \sum_s \tilde{L}_{sc}$. This setting does not deliver an aggregate production function depending on aggregate stocks of human capital alone. I define the *aggregate relative skill efficiency* as

$$\left(\frac{w_{Hc}}{w_{Lc}}\right)^{\frac{1}{\rho}}\left(\frac{\tilde{H}_{c}}{\tilde{L}_{c}}\right)^{\frac{1-\rho}{\rho}} = \left(\sum_{s}\frac{\tilde{L}_{c,s}}{\tilde{L}_{c}}\left(\frac{w_{Hc}/w_{Lc}}{w_{Hc,s}/w_{Lc,s}}\right)^{\frac{1}{1-\rho}}\left(\frac{A_{Hc,s}Q_{Hc,s}}{A_{Lc,s}Q_{Lc,s}}\right)^{\frac{\rho}{1-\rho}}\right)^{\frac{1-\rho}{\rho}} \quad (8)$$

which is the quantity that would be backed out in an exercise like the one in Section 3.2, that ignores sectorial heterogeneity.

Equation (8) provides some structure to think about how the inferred relative skill efficiency depends on sectorial composition. Relative skill efficiency is a weighted combination of sector-specific relative skill efficiencies and wage gaps. In a model with perfect labor mobility across sectors, wages will be equalized by skill level; however, in reality compensating differentials and mobility frictions can prevent full wage equalization. Aggregate relative skill efficiency is higher in countries where a larger share of the unskilled labor force is employed in sectors with high relative skill efficiency. Moreover, it is higher when these sectors have a relatively lower skill premium, implying that relatively more skilled workers work in those sectors.

I measure the various components (8) with data on wages and human capital at the sectorial level. I consider 11 broad sectors that can be consistenly defined across all 12 countries. When constructing human capital stocks, I follow exactly the same procedure as in Section 3.2.[10]

I find that relative skill efficiency does vary significantly across sectors, and the ranking of the sectors in terms of relative skill efficiency is similar across countries. Moreover, rich countries are tend to have larger employment shares in sectors with high relative skill-efficiency, such as financial and business services. To illustrate this point, column 2 of Table IV shows the results of a simple counterfactual exercise, where each country is assigned the employment shares of the US, $\frac{\tilde{L}_{US,s}}{\tilde{L}_{US}}$. For several countries, this reduces the gap in relative skill efficiency considerably. However, large differences are present even within sectors. As shown in column 3, closing wage gaps across sectors mostly reduces cross-country gaps in relative skill efficiency.

An important caveat is in order. The discussion and results in this section rely on the elasticity of substitution estimated by Ciccone and Peri (2006) being valid at the sectorial level. However, sectorial and aggregate elasticities will generally differ. In particular, the aggregate elasticity will be a combination of the sectorial one and the elasticity of demand between sectors (Oberfield and Raval, 2014). If the demand is elastic enough, the sector-level elasticity will be smaller than ρ, potentially implying a larger role for sectorial composition. I leave a thorough examination of this possibility to future work.

[10] I do not use sector-specific returns to experience, gender and education when constructing human capital stocks in order to preserve the equivalence of the relative skill bias inferred from equation (8) and equation (4). Using sector-specific parameters has a negligible impact on the results.

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 skill efficiency, with richer and more skill-abundant countries having relatively more efficient skilled labor. This pattern, both qualitatively and quantitatively, does not appear to be an artifact of measurement issues. This leads naturally to the next question: what explains the variation in relative skill efficiency across countries? In this section I consider how migrants can help anwering this question.

My strategy is based on the analysis of immigrants educated in different countries and observed in the same labor market. I first modify the baseline framework to include a specific role for workers' country of origin. I then map the new framework to the data and discuss the emerging patterns.

4.1 A Modified Framework

I introduce a new dimension of workers' heterogeneity to the framework in Section 3.1: 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 skilled and unskilled workers' embodied human capital depends on the country where their education was acquired (indexed by a). This might reflect the combined impact of several characteristics 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 wish (or need) to take a stand on the source of embodied productivity differences between skilled and unkilled 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 different immigrant groups are assumed to be (i) perfect substitutes and (ii) augmented by the same technology. I will examine possible issues with both these assumptions in Section 5. The production function is of the type

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

The total quantities of high- and low-skill services used for production in country c are

$$H_c = \sum_a Q^a_{Hc}\tilde{H}^a_c \tag{9}$$

$$L_c = \sum_a Q^a_{Lc}\tilde{L}^a_c \tag{10}$$

where $\tilde{H}_c^a$ and $\tilde{L}_c^a$ are the number of (baseline equivalent) skilled and unskilled workers educated in country a and working in c, and Q_{Hc}^a and Q_{Lc}^a represent their average quality. No further assumption on the shape of the production function or the human capital aggregator is necessary.

In a competitive labor market, the wage ratio between skilled and unskilled workers educated in a generic country b is

$$\frac{w_{Hc}^b}{w_{Lc}^b} = \frac{A_{Hc}Q_{Hc}^b}{A_{Lc}Q_{Lc}^b}\frac{F_H\left(A_{Kc}K_c, A_{Lc}L_c, A_{Hc}H_c\right)}{F_L\left(A_{Kc}K_c, A_{Lc}L_c, A_{Hc}H_c\right)} \tag{11}$$

This expression summarizes the key source of variation for my empirical strategy. Immigrant groups educated in their home countries face similar labor market conditions, both in terms of the degree of technological skill bias ($\frac{A_{Hc}}{A_{Lc}}$) and of the 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 isolate cross-nationality differences in the relative quality of skilled and unskilled labor.

4.2 Measurement

In this section I describe how I map this framework to the data. The objective is to separately identify $\frac{A_{Hc}}{A_{Lc}}$ and $\frac{Q_{Hc}^c}{Q_{Lc}^c}$, in order to study the variability of both across countries. I normalize $\frac{A_{Hc}}{A_{Lc}}$ and $\frac{Q_{Hc}^c}{Q_{Lc}^c}$ so that they are 1 for the US.

I focus on the native and foreign-born workers living in the United States, observed in the 2000 Census. I restrict attention to workers between 15 and 64 years old, who have been working for wages for at least 30 weeks and 30 hours per week in the previous year. To isolate the role of education in the origin country, I only consider immigrants which are 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.

As before, I assume non interactive effects of education, gender and experience on workers' efficiency, so that

$$\begin{aligned}\tilde{H}_c^a &= \sum_{j\in H}\sum_g\sum_{exp} e^{\beta_{cj}^a}e^{\lambda_{cg}^a}e^{\mu_{c,exp}^a}n_{c(j,g,exp)}^a \\ \tilde{L}_c^a &= \sum_{j\in L}\sum_g\sum_{exp} e^{\beta_{cj}^a}e^{\lambda_{cg}^a}e^{\mu_{c,exp}^a}n_{c(j,g,exp)}^a\end{aligned} \tag{12}$$

where $n_{c(j,g,exp)}^a$ is the number of workers in group (j, g, exp) educated in country a. The coefficients on education, experience and gender vary by country of origin, to reflect that they might include the effect of human capital quality or technology.[11] The average log wage of a worker educated in a, of skill $S \in \{H, L\}$, with educational attainment j, gender g and experience exp is:

$$\log w^a_{Sc(j,g,exp)} = \alpha_c + \gamma_{Sc} + \log Q^a_{Sc} + \beta^a_j + \lambda^a_g + \mu^a_{exp} \tag{13}$$

where α_c is a constant and $\gamma_{Sc} = \log F_S(A_{Kc}K_c, A_{Lc}L_c, A_{Hc}H_c)$. In a specification including skill group fixed effects, the interaction terms between skill group and country of origin fixed effects (with US natives as omitted category) identify $\log Q^a_{S,US} - \log Q^{US}_{S,US}$ for $S \in \{H, L\}$, from which $\log \frac{Q^a_{H,US}}{Q^a_{L,US}}$ can be calculated (recall that $\log \frac{Q^{US}_{H,US}}{Q^{US}_{L,US}}$ is normalized to 1). Moreover, β^a_{cj}, λ^a_{cg} and $\mu^a_{c,exp}$ are identified from country-of-origin-specific coefficients on educational attainment, gender and experience fixed effects.

Under the assumption that the relative quality of skilled workers among US immigrants captures the relative quality among natives in the country origin, that is $\log \frac{Q^a_{H,US}}{Q^a_{L,US}} = \log \frac{Q^a_{Ha}}{Q^a_{La}}$, I can examine the cross-country variation in the latter. The main question of interest is the role of relative skill quality in explaining differences in relative skill efficiency. Given that workers' quality is assumed to be heterogeneous depending of the country in which they were educated, in principle one should take into account the educational composition of the population in each country when computing relative skill quantities and backing out relative efficiencies. However, if immigrants educated abroad are a sufficiently small share of the working population, the relative supply, quality and price of skills among native workers are good approximations for the corresponding population-wide quantities.[12] I rely on this approximation and compute for each country $\frac{A_{Hc}}{A_{Lc}}$ from (4), using estimates for the relative skill quality among native workers.[13,14] From now on, I simply refer to these objects as $\frac{A_H}{A_L}$

[11]Bratsberg (2002) and Schoellman (2012) document differences in country of origin-specific Mincerian returns for US immigrants, while Lagakos et al. (2016) argue for country-specific returns to experience. Note that the heterogeneity of the relative quality of skilled and unskilled labor already implies heterogeneous Mincerian returns. In future work, I plan to examine more systematically the extent to which heterogeneous returns to schooling are driven by differences within as opposed to between skill groups.

[12]More precisely, the population-wide skill premium is given by

$$\frac{w_{Hc}}{w_{Lc}} = \left(\frac{A_{Hc}Q_{Hc}}{A_{Lc}Q_{Lc}}\right)^{\rho} \left(\frac{\sum_a (Q^a_{Hc}/Q_{Hc})\tilde{H}^a_c}{\sum_a (Q^a_{Lc}/Q_{Lc})\tilde{L}^a_c}\right)^{\rho-1}$$

where, for $S \in \{H, L\}$, $w_{Sc} = \sum_a w^a_{Sc}\frac{n^a_{Sc}}{n_{Sc}}$, $Q_{Sc} = \sum_a Q^a_{Sc}\frac{n^a_{Sc}}{n_{Sc}}$ and n_{Sc} (n^a_{Sc}) is the number of workers of skill S in the population (educated in country a). If $n^c_{Sc} \approx n_{Sc}$ for $S \in \{H, L\}$, then clearly $\frac{w_{Hc}}{w_{Lc}} \approx \frac{w^c_{Hc}}{w^c_{Lc}}$, $\frac{Q_{Hc}}{Q_{Lc}} \approx \frac{Q^c_{Hc}}{Q^c_{Lc}}$ and $\frac{\sum_a (Q^a_{Hc}/Q_{Hc})\tilde{H}^a_c}{\sum_a (Q^a_{Lc}/Q_{Lc})\tilde{L}^a_c} \approx \frac{\tilde{H}^c_c}{\tilde{L}^c_c}$.

[13]The Barro and Lee (2013)'s data, used to compute human capital stocks, refer to the whole population (natives and immigrants). The skill premium estimated from IPUMS data is relative to native workers only (though including immigrants has a negligible impact on the resulting estimates).

[14]In principle, using data on the stock of migrants by country of origin, one could make some progress towards quantifying the importance of differences in the ethnic composition of the population. This approach

and $\frac{Q_H}{Q_L}$.

To summarize the empirical strategy, I start from a difference-in-differences approach, where I compare, within the United States, the log wages of skilled and unskilled workers between the different countries where they were educated. I then examine whether skill premia are larger for countries of origin with a higher measured relative efficiency of skilled labor, and draw the implications for the cross-country dispersion in the latter.

4.3 Results

In this section I show how the relative skill bias of technology and quality of skilled labor vary across countries. I start from focusing on the 12 countries for which I have the micro data to compute relative skill efficiency. Table V shows the patterns for skill efficiency, technology bias and skill quality. Relative skill qualtity is estimated to be increasing with respect to GDP per capita, consistently with the results on Mincerian returns in Schoellman (2012). However, the slope of these relationships is quite small compared to one relative to overall skill efficiency. As a consequence, cross-country variation the technology term dwarfs the quality one. Figure III illustrates that the relative skill bias of technology is strongly increasing in GDP per worker, while the relative quality term is only mildly so.

This result is driven by the fact that the magnitude of the variation of the skill premium across migrants' nationalities is small. Figure shows that this conclusion is not specific only to the 12 countries in my sample. Here I compute relative skill quality for 42 countries for which I have a sufficient number of migrants (at least 100 skilled and 100 unskilled), and I plot it agains log GDP per capita. There is once again a positive relationship, with a slope similar to the one found in the smaller sample.

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.

would require, across different host countries, information on the composition by education and age of arrival of the stock of migrants from each country of origin, and assumptions on the quality of individuals whose educational career spans more than one country. Given the substantial data requirements, the additional structure that this would involve and the fact the immigrants educated abroad are a small share of the population in most countries, I chose not to follow this route.

5.1 Selection

Given that my strategy consists of using immigrant workers to estimate country-specific differences in the relative quality of skilled labor, a natural concern is that emigrant workers are not randomly selected. In this section I discuss the possible consequences of selection and discuss some evidence on its importance.

It is helpful to explicitly introduce some individual-level heterogeneity in the framework of section 4.1 to illustrate the main issues. Suppose that the quality of individual i, of skill $S \in \{H, L\}$, having completed his education in country a is $Q_S^a \varepsilon_{S,i}^a$, where Q_S^a is a term common to all individuals of skill S educated in a and $\varepsilon_{S,i}^a$ captures the heterogeneity in unobservable skills. For analytical convenience, I assume that $\varepsilon_{S,i}^a$ follows a log-normal distribution with log-mean 0 and log-variance $(\sigma^a)^2$. Moreover, I mantain the assumption that $\varepsilon_{S,i}^a$ is uncorrelated with workers' observable characteristics (education, gender and experience).[15]

If migrants are selected on unobservable skills, $\mathbb{E}\left[\log \varepsilon_{S,i}^a | \text{migrant}\right] \neq 0$. The relative log skill quality I estimate out of US migrants using (12) would then read

$$\log Q_{H,US}^a - \log Q_{L,US}^a = \log Q_H^a - \log Q_L^a + \mathbb{E}\left[\log \varepsilon_{H,i}^a | \text{migrant}\right] - \mathbb{E}\left[\log \varepsilon_{L,i}^a | \text{migrant}\right] \tag{14}$$

which differs from the quantity of interest as long as $\mathbb{E}\left[\log \varepsilon_{H,i}^a | \text{migrant}\right] \neq \mathbb{E}\left[\log \varepsilon_{L,i}^a | \text{migrant}\right]$. Migrants' selection is therefore problematic to the extent that it takes place with a different degree across skill groups.

Since my main result is that, for most countries, the log relative quality of skilled labor inferred out of migrants is too large to account for the international gaps in skill efficiency, investigating the possibility that $\mathbb{E}\left[\log \varepsilon_{H,i}^a | \text{migrant}\right] > \mathbb{E}\left[\log \varepsilon_{L,i}^a | \text{migrant}\right]$ is of particular interest. A more positive degree of selection across skilled workers could in principle lead me to understate the importance of relative skill quality differences across countries.

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. on how, among individuals educated in a given country, the degree of selection on unobservables of migrants within the low-skill group compares to the one within the high-skill group, has received far less attention. Recent evidence comes from Schoellman and Hendricks (2017), 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

[15] This is obviously a strong assumption, though common in the development accounting literature. See footnote 8 for a related discussion.

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 high-school dropouts and college educated roughly correspond to[16]

$$Selection_L = \exp\left(\mathbb{E}\left[\log \varepsilon^a_{L,i} | \text{migrant}\right]\right) \tag{15}$$

$$Selection_H = \exp\left(\mathbb{E}\left[\log \varepsilon^a_{H,i} | \text{migrant}\right]\right) \tag{16}$$

so that by taking

$$\log\left(\frac{Selection_L}{Selection_H}\right) = \mathbb{E}\left[\log \varepsilon^a_{H,i} | \text{migrant}\right] - \mathbb{E}\left[\log \varepsilon^a_{L,i} | \text{migrant}\right]$$

I obtain the country-specific factor I need to correct for the selection bias in (14). Table VI shows the results when the estimates for $\frac{Q_H}{Q_L}$ are corrected for selection. For most countries this correction results in higher estimates for skill quality, and overall the relationship between relative skill quality and GDP per capita becomes flatter. This reflects the fact that, in most cases, skilled migrants are more adversely selected than unskilled migrants.

I discuss one piece of evidence consistent with this pattern of differential selection: the propensity to migrate conditional on skill group is much higher for the high-skilled than for the low-skilled. Figure IV plots the share of skilled workers among US emigrants for each country of origin against the share of skilled workers in the country of origin population. Almost all countries are above the 45 degree line, showing that emigrants are substantially more likely to be high-skilled.[17] If, as suggested by the literature, migrants' selection on unobservables (conditional on observables) is positive, such a pattern would imply that skilled migrants are relatively more negatively selected. To see why, suppose there exists a skill-specific threshold t^a_S such that workers migrate if $Q^a_S \varepsilon^a_{S,i} \geqslant t^a_S$. The within-skill group share of emigrants is then $1 - \Phi\left(\frac{\log t^a_S - \log Q^a_S}{\sigma^a}\right)$, where $\Phi(.)$ is the standard Normal's cumulative distribution function. The fact that $1 - \Phi\left(\frac{\log t^a_H - \log Q^a_H}{\sigma^a}\right) > 1 - \Phi\left(\frac{\log t^a_L - \log Q^a_L}{\sigma^a}\right)$, implied by Figure IV, means that $\log t^a_H - \log Q^a_H < \log t^a_L - \log Q^a_L$. It follows that

$$\mathbb{E}\left[\log \varepsilon^a_{H,i} | \text{migrant}\right] = \frac{\sigma^a \phi\left(\frac{\log t^a_H - \log Q^a_H}{\sigma^a}\right)}{1 - \Phi\left(\frac{\log t^a_H - \log Q^a_H}{\sigma^a}\right)} < \mathbb{E}\left[\log \varepsilon^a_{L,i} | \text{migrant}\right] = \frac{\sigma^a \phi\left(\frac{\log t^a_L - \log Q^a_L}{\sigma^a}\right)}{1 - \Phi\left(\frac{\log t^a_L - \log Q^a_L}{\sigma^a}\right)}$$

Intuitively, if migrating is relatively easier for high-skilled individuals, the low-skilled ones

[16]Schoellman and Hendricks (2017) net out effect of observable characteristics by using US data to estimate their impact on wages, as opposed to country-specific data as it would be more appropriate in my setting. Moreover, as already mentioned, their reported measures of selection vary at the GDP-group level (less than 1/16, between 1/16 and 1/8, 1/8 and 1/4, 1/4 and 1/2, and more than 1/2 of US GDP per capita).

[17]Similar patterns hold when expressing units in terms of baseline equivalent workers as opposed to counting persons.

who do migrate should be comparatively better selected on unobservable skills.

I conclude this section by noting that the threat of selection is less severe when comparing countries other than the United States. This is because, while US estimates are based on native workers, for all other countries the relative skill quality is inferred from immigrants only. Cross-country gaps in these estimates capture actual gaps in relative skill quality as long as there is not a pattern of *differential relative selection* of skilled and unskilled migrants across countries, while a common degree of relative selection in unconsequential. As it is evident from Figure III, the result that technology skill bias (as opposed to relative skill quality) is the key factor varying between poor and rich countries is not driven by the United States only.

5.2 Skill Downgrading

Another concern is that emigrant workers might not utilize their skills to the same extent as they would if they were employed in their origin country. First, they *might be unable* to do so, because part of their human capital is country-specific (language, knowledge of the institutional environment, fit between the educational curriculum and the work environment) or because they face frictions that prevent them to access the occupation where their expertise would be most valued. Second, they *might not be willing* to do so, because their comparative advantage in the host country labor market is in activities that do not require the full utilization of their skills (Jones, 2014).

These two theories have opposite implications in terms of the bias induced by my empirical approach. If migrants were unable to fully utilize their skills, the productivity gap between skilled and unskilled migrants would be muted, and this would be reflected in a relatively low skill premium. My approach would tend to underestimate relative skill quality for nationalities for which this is more the case. On the contrary, if skilled migrants with low unobservable skill quality optimally selected low-skilled occupations when in a country with abundance of high quality skilled labor, my approach would overestimate the relative skill quality for the nationalities for which skill downgrading is more prevalent (skilled migrants from those countries would enjoy a lower premium if *forced* to work in a more skill-intensive position).

I propose a measure of skill downgrading in order to explore this issue. Since I do not observe the pre-migration occupation or field of specialization, my measure is based on the skill intensity of skilled migrants' occupation in the US. In particular, for individual i, educated in country a and employed in occupation o in the US, I define

$$\textit{Skill Downgrading}^a_{i,o,US} = \frac{s^a_{i,o,US}}{\bar{s}^{US}_{o,US}}$$

where $s^a_{i,o,US}$ represents i's completed years of schooling and $\bar{s}^{US}_{o,US}$ is the average years of schooling completed by US natives who are employed in occupation o. A value greater than 1 suggests that a migrant is over-qualified for the job, and might not be fully utilizing his or her skills.

Figure V displays the average of the proxy for skill downgrading for skilled workers across countries of origin, against log relative skill efficiency.[18] First notice that, consistently with the evidence in Jones (2014), migrants are on average more qualified than US natives conditional on occupation. The extent of skill downgrading is decreasing in the relative productivity of skill labor in the country of origin.

Is country-specific human capital an important factor in determining the extent of skill downgrading? Table VII examines this for countries in the sample for which I can construct relative skill efficiency using micro data. The first column showns that, conditional on education, experience, gender and country of origin fixed effects, migrants that have spent more time in the US are less subject to skill downgrading. This is consistent with the view that migrants lack the country-specific skills or connections to work in an occupation appropriate for their educational level, and that they make up for this disadvantage as they integrate in the new country. The second column provides evidence on a specific dimension of country-specific human capital by showing that linguistic distance between migrants' country of origin and the United States, as measured in Spolaore and Wacziarg (2015), is positively correlated with skill downgrading. Finally, the third column shows that years in the US and linguistic distance retain their significance when included simultaneously, and that conditioning on them attenuates the correlation between skill downgrading and relative skill efficiency in the country of origin.

Overall, the results in this section suggest that skill downgrading at least partially reflects the non-transferability of human capital across countries, implying that the skill premium would tend to underestimate relative skill quality for those countries of origin more subject to it. Since these are countries with low relative skill efficiency, this pattern of skill downgrading reinforces my conclusion that relative skill quality is unlikely to explain a large part of the cross-country variation in relative skill efficiency.

[18] In principle one can build the corresponding measure for unskilled workers as well, and examine the extent of skill downgrading (or upgrading) in this group. In practice this is problematic because most unskilled workers from developing countries have levels of education below the natives' average in *any* occupation in the US, so that my measure would imply by construction large degrees of skill upgrading. This is not the case for skilled migrants, who arrive to the US with levels of education more in line with those of US natives. A thourough investigation of the different extents of educational and occupational overlap across countries, as well as differences in the mapping between educational achievements and occupations is an important task left for future work (see Porzio (2017) for recent progress in this direction).

5.3 Sorting

Comparing skill premia across nationalities identifies relative skill quality if migrants use the same technology and face the same relative price of skilled and unskilled efficiency units. This might not be the case if there is heterogeneity within the United States in these factors, and if migrants from different nationalities sort into sectors or labor markets that systematically differ along these lines.

I consider two types of within country heterogeneity: sectors and regions. Consider first an environment with a sector-specific production technology,

$$Y_{sc} = A_{sc} F\left(A_{Ksc} K_{sc}, A_{Lsc} L_{sc}, A_{Hsc} H_{sc}\right)$$

where L_{sc} and H_{sc} aggregate skilled and unskilled efficiency units supplied by natives and immigrants from different nationalities as in Section 4.1. The wage ratio between skilled and unskilled workers educated in a generic country b and employed in sectors r and s is

$$\frac{w^b_{Hrc}}{w^b_{Lrc}} = \frac{A_{rc} A_{Hrc} Q^b_{Hrc}}{A_{sc} A_{Lsc} Q^b_{Lsc}} \frac{F_H\left(A_{Krc} K_{rc}, A_{Lrc} L_{rc}, A_{Hrc} H_{rc}\right)}{F_L\left(A_{Ksc} K_{sc}, A_{Lsc} L_{sc}, A_{Hsc} H_{sc}\right)} \tag{17}$$

Equation (17) 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 A_{sc}. This means that there is a sector-specific component in wages, which can be identified by a sector fixed effect in a log-wage regressions. On the other hand, migrants could be differentially sorting into sectors with different skill bias of technology or relative prices of skilled and unskilled efficiency units. This would imply different skill premia across sectors.

In a world with perfect labor mobility, for a given skill category and a given level of skill quality wages would be equalized across sectors, so that the concerns above would not apply. However, this might not happen in reality for a number of reasons, including compensating differentials and mobility frictions. I therefore examine whether my inference on nationality-specific skill quality is affected by augmenting (13) with sector-specific and sector-skill-specific dummies,

$$\log w^a_{Ssc(j,g,exp)} = \alpha_{sc} + \gamma_{Ssc} + \log Q^a_{Sc} + \beta^a_j + \lambda^a_g + \mu^a_{exp} \tag{18}$$

where α_{sc} identifies $\log A_{sc}$ and γ_{Ssc} identifies $\log A_{Ssc} F_S\left(A_{Ksc} K_{sc}, A_{Lsc} L_{sc}, A_{Hsc} H_{sc}\right)$.

Column 3 of Table VIII shows the resulting estimates for relative skill quality. Allowing for sectoral heterogeneity has a negligible impact both on the cross-country variation and the overall magnitude of the results (compared to the benchmark estimates reported in column

2). While sectors are heterogeneous in terms of technology and skill prices, the allocation of migrants across sectors does not appear to be systematically related to these factors.

In column 4 of Table VIII I report the results of the corresponding exercise by region. In particular, I estimate (17) introducing commuting zones fixed effects, as well as interactions between those and the skilled dummy. Once again, the impact of this adjustment is minimal.

6 Conclusions

In this paper I re-visit the question of how the relative productivity of skilled and unskilled labor differs across countries. I show that, according to various sources, the skill premium varies little across countries, implying large gaps in relative skill efficiency. In the second part of the paper, I show that skill premia within immigrant groups are not consistent with the view that differences in relative skill quality play a quantitatively important role. The variation in relative skill efficiency is instead more likely to be related to technological factors.

These results have important implications when considering the relative role of human capital and technology in accounting for cross-country differences in output per worker. Malmberg (2017) suggests that gaps in skill efficiency are an important component of differences in economic performance. My findings imply that one should be careful in attributing these gains to human capital. Moreover, if we accept the view that the factor-bias of adopted technologies is very different between rich and poor country, this gives credit to the possibility that rich countries' technologies might not be appropriate for firms in poor countries, as argued by Acemoglu and Zilibotti (2001).

Indeed, my results emphasize the importance of understanding the determinants of technological skill bias. A common view is that differences in the technology mix reflect the optimal responses of firms to the abundance or scarcity of skilled labor (Caselli and Coleman, 2006). It would be useful to have a sense of the quantitative importance of this mechanism, and of whether other institutional, cultural or geographical factors might contribute to explain why poorer countries adopt less skill-biased technologies.

The approach of this paper can be extended in various directions. For example, it would be interesting to explore the relative role of technology and human capital in explaining the differential evolution of the skill premium over time in the United States and Europe. Moreover, a similar exercise could be performed within countries, in order to explore how relative skill quality vary across regions with different characteristics. I hope to address some of these open issues in future work.

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Tables

Table I: Skill Premium, Supply and Efficiency across Countries

		Baseline		No Hours	All Working Age	Mincerian
Country	w_H/w_L	$\tilde{H}/\tilde{L}$	$(A_H Q_H)/(A_L Q_L)$	$(A_H Q_H)/(A_L Q_L)$	$(A_H Q_H)/(A_L Q_L)$	$(A_H Q_H)/(A_L Q_L)$
Jamaica	5.21	0.04	0.02	0.03	0.08	-
Indonesia	4.68	0.05	0.02	0.02	0.06	0.01
Trinidad and Tobago	3.88	0.08	0.02	0.03	0.07	-
Venezuela	4.25	0.09	0.03	0.05	0.09	0.03
Brazil	4.50	0.12	0.08	0.11	0.15	0.04
India	3.65	0.13	0.05	0.06	0.11	0.01
Mexico	3.30	0.16	0.06	0.08	0.12	0.03
Panama	3.23	0.21	0.09	0.11	0.16	0.16
Uruguay	3.12	0.27	0.14	0.17	0.20	0.03
Israel	2.20	0.44	0.13	0.16	0.20	0.47
Canada	2.12	1.08	0.67	0.78	0.82	0.10
United States	2.02	1.42	1	1	1	1
Elasticity w/GDP p.c.	-0.295***	1.001***	1.117***	1.046***	0.765***	1.745***
	(0.072)	(0.258)	(0.332)	(0.304)	(0.223)	(0.365)

Notes: The Table shows the 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. Columns 3-6 display the relative skill efficiency obtained by not weighting workers by hours worked, including all working age population irrespective of employment status (and hours worked) and using Mincerian returns from Caselli et al. (2016) to impute the skill premium and calibrate the human capital stocks. The last row show the coefficient of a regression of the log of each variable and log GDP per capita.

Table II: Relative Skill Efficiency - Robustness

	$(A_H Q_H)/$ $(A_L Q_L)$			
	Baseline	Skilled Threshold: Secondary Completed	Skilled Threshold: Tertiary Completed	Three Skill Groups
Jamaica	0.02	0.05	0.01	0.01
Indonesia	0.02	0.01	0.01	0.01
Trinidad and Tobago	0.02	0.04	0.01	0.02
Venezuela	0.03	0.01	0.01	0.02
India	0.05	0.01	0.04	0.01
Mexico	0.06	0.01	0.06	0.01
Brazil	0.08	0.02	0.08	0.02
Panama	0.09	0.01	0.10	0.02
Israel	0.13	0.11	0.08	0.07
Uruguay	0.14	0.01	0.04	0.02
Canada	0.67	0.16	0.23	0.19
United States	1	1	1	1
Elasticity w/GDP p.c.	1.117***	1.481***	1.052	1.224***
	(0.332)	(0.397)	(0.619)	(0.322)

Notes: The Table shows the the relative skill efficiency across the countries in the sample. Relative skill efficiency is normalised such that it takes value 1 for the United States. Column 2 reports the baseline estimate, and columns 3-5 show results when the educational threshold for skilled workers is set to secondary complete (column 3), tertiary complete (column 4) and when the groups less than secondary, secondary and some tertiary are assumed to be imperfect substitutes (column 5). The last row show the coefficient of a regression of the log of each variable and log GDP per capita.

Table III: Relative Skill Efficiency: the Role of Self-Employment

Country	Wage Workers Only			Wage Workers and Self-Employed		
	w_H/w_L	$\tilde{H}/\tilde{L}$	$(A_H Q_H)/$ $(A_L Q_L)$	w_H/w_L	$\tilde{H}/\tilde{L}$	$(A_H Q_H)/$ $(A_L Q_L)$
Trinidad and Tobago	3.88	0.08	0.02	4.28	0.09	0.04
Panama	3.23	0.21	0.09	3.79	0.23	0.16
Canada	2.12	1.08	0.67	2.11	1.08	0.63
United States	2.02	1.42	1	2.03	1.44	1

Notes: The Table shows the 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. Columns 1-3 display the baseline results, while columns 4-6 display results when self-employment income is included in the computation of skill premia and calibration of human capital stocks.

Table IV: Relative Skill Efficiency - Sectoral Composition

	Aggregate Relative Skill Efficiency		
	Baseline	US Sectorial Shares	US Sectorial Shares + No Wage Gaps
Jamaica	0.02	0.02	0.02
Indonesia	0.02	0.15	0.04
Trinidad and Tobago	0.02	0.03	0.03
Venezuela	0.03	0.05	0.06
India	0.05	0.32	0.17
Mexico	0.06	0.07	0.07
Brazil	0.08	0.09	0.08
Panama	0.09	0.13	0.12
Israel	0.13	0.14	0.15
Uruguay	0.14	0.14	0.13
Canada	0.67	0.81	0.73
United States	1	1	1
Elasticity w/GDP p.c.	1.117***	0.459	0.784*
	(0.332)	(0.403)	(0.363)

Notes: The Table shows the the aggregate 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. Column 1 reports the baseline estimate, column 2 the counterfactual estimate obtained by assigning to each country the US employment shares and column 3 the one obtained by closing skill premia gaps across sectors. The last row show the coefficient of a regression of the log of each variable and log GDP per capita.

Table V: Relative Technology and Skill Quality across Countries

Country	$\frac{A_H Q_H}{A_L Q_L}$	$\frac{A_H}{A_L}$	$\frac{Q_H}{Q_L}$
Indonesia	0.02	0.02	0.69
India	0.05	0.07	0.73
Venezuela	0.03	0.05	0.75
Mexico	0.06	0.08	0.76
Brazil	0.08	0.10	0.82
Uruguay	0.14	0.19	0.74
Jamaica	0.02	0.02	0.78
Panama	0.09	0.12	0.77
Trinidad and Tobago	0.02	0.03	0.72
Israel	0.13	0.14	0.91
Canada	0.67	0.71	0.95
United States	1.00	1.00	1.00
Elasticity w/GDP p.c.	1.117***	1.008***	0.109***
	(0.332)	(0.316)	(0.026)

Notes: The Table shows relative skill efficiency, relative skill bias of technology and relative skill quality across the countries in the sample. All variables are normalised such that they take value 1 for the United States. The last row show the coefficients of a regression of the log of each variable on log GDP per capita.

Table VI: Relative Technology and Skill Quality across Countries Corrected for Selection

Country	$\frac{A_H Q_H}{A_L Q_L}$	$\frac{A_H}{A_L}$	$\frac{Q_H}{Q_L}$
Indonesia	0.02	0.03	0.65
India	0.05	0.06	0.85
Venezuela	0.03	0.04	0.95
Mexico	0.06	0.06	0.95
Brazil	0.08	0.08	0.98
Uruguay	0.14	0.15	0.93
Jamaica	0.02	0.02	0.94
Panama	0.09	0.10	0.98
Trinidad and Tobago	0.02	0.03	0.91
Israel	0.13	0.15	0.84
Canada	0.67	0.77	0.87
United States	1	1	1
Elasticity w/GDP p.c.	1.117***	1.061***	0.056
	(0.332)	(0.332)	(0.039)

Notes: The Table shows relative skill efficiency, relative skill bias of technology and relative skill quality across the countries in the sample, corrected for selection as discussed in the text. All variables are normalised such that they take value 1 for the United States. The last row show the coefficients of a regression of the log of each variable on log GDP per capita.

Table VII: The Determinants of Skill Downgrading

	Dependent variable: Skill Downgrading		
	[1]	[2]	[3]
Years in US	-0.001**		-0.001*
	(0.000)		(0.000)
Linguistic Distance		0.052**	0.040***
		(0.017)	(0.009)
Log Relative Skill Efficiency			-0.053***
			(0.016)
N	27936	27936	27936
R Squared	0.45	0.43	0.44
Controls	Yes	Yes	Yes
Origin Country FE	Yes	No	No

Notes: The sample is restricted to US immigrants from countries for which I can estimate relative skill efficiency, educated in their country of origin (as defined in the main text). *Skill Downgrading* is the ratio between own years of schooling and average years of schooling among US natives employed in the same occupation. *Linguistic Distance* is computed between the US and the migrant's country of origin. *Log Relative Skill Efficiency* refers to each migrant's country of origin. *Controls* include education, experience and gender dummies. Observations weighted according to the provided sample weights. Robust standard errors clustered by country of origin. * denotes significance at 10%, ** at 5%, *** at 1%.

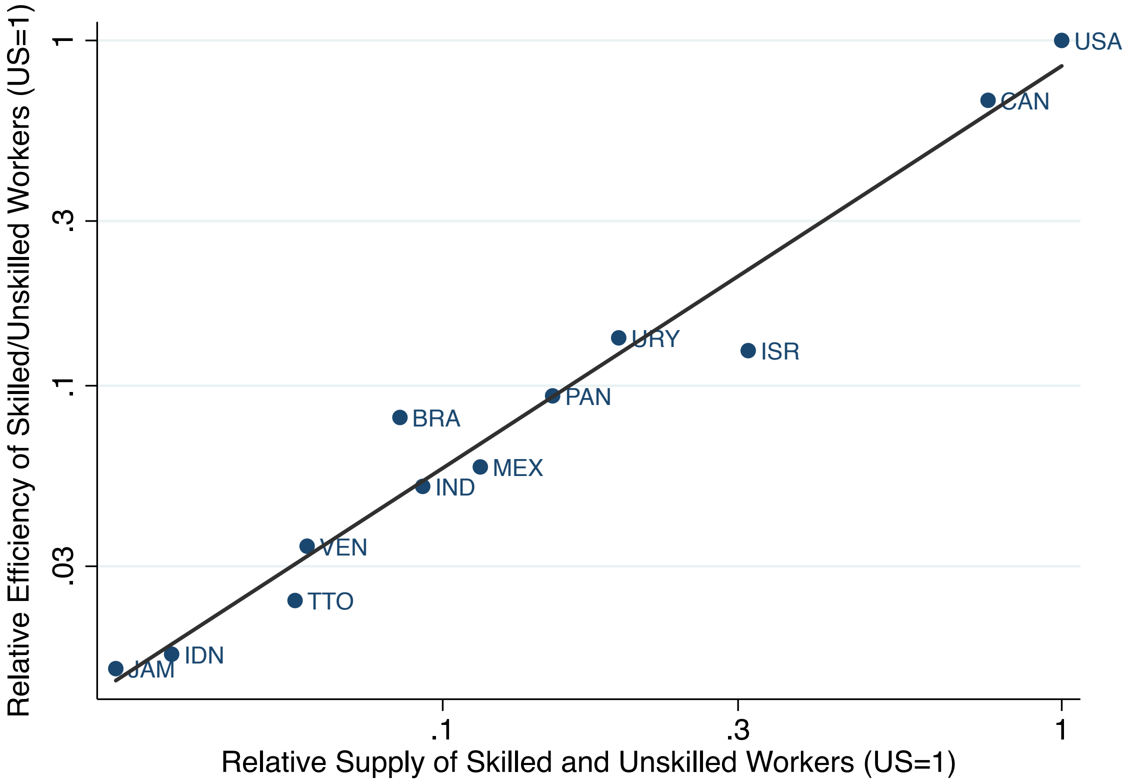
Table VIII: Relative Technology and Skill Quality across Countries - Sorting

Country	$\frac{A_H Q_H}{A_L Q_L}$	Baseline $\frac{Q_H}{Q_L}$	Sorting by Sector $\frac{Q_H}{Q_L}$	Sorting by Region $\frac{Q_H}{Q_L}$
Indonesia	0.02	0.69	0.66	0.67
India	0.05	0.73	0.72	0.71
Venezuela	0.03	0.75	0.73	0.74
Mexico	0.06	0.76	0.76	0.74
Brazil	0.08	0.82	0.82	0.80
Uruguay	0.14	0.74	0.76	0.77
Jamaica	0.02	0.78	0.79	0.81
Panama	0.09	0.77	0.75	0.76
Trinidad and Tobago	0.02	0.72	0.73	0.75
Israel	0.13	0.91	0.90	0.89
Canada	0.67	0.95	0.97	0.98
United States	1	1	1	1
Elasticity w/GDP p.c.	1.117***	0.109***	0.102***	0.103***
	(0.332)	(0.026)	(0.030)	(0.028)

Notes: The Table shows relative skill efficiency and relative skill bias of technology corrected for sorting by sector (Column 3) and by commuting zones (Column 4) as discussed in the text. All variables are normalised such that they take value 1 for the United States. The last row show the coefficients of a regression of the log of each variable on log GDP per capita.

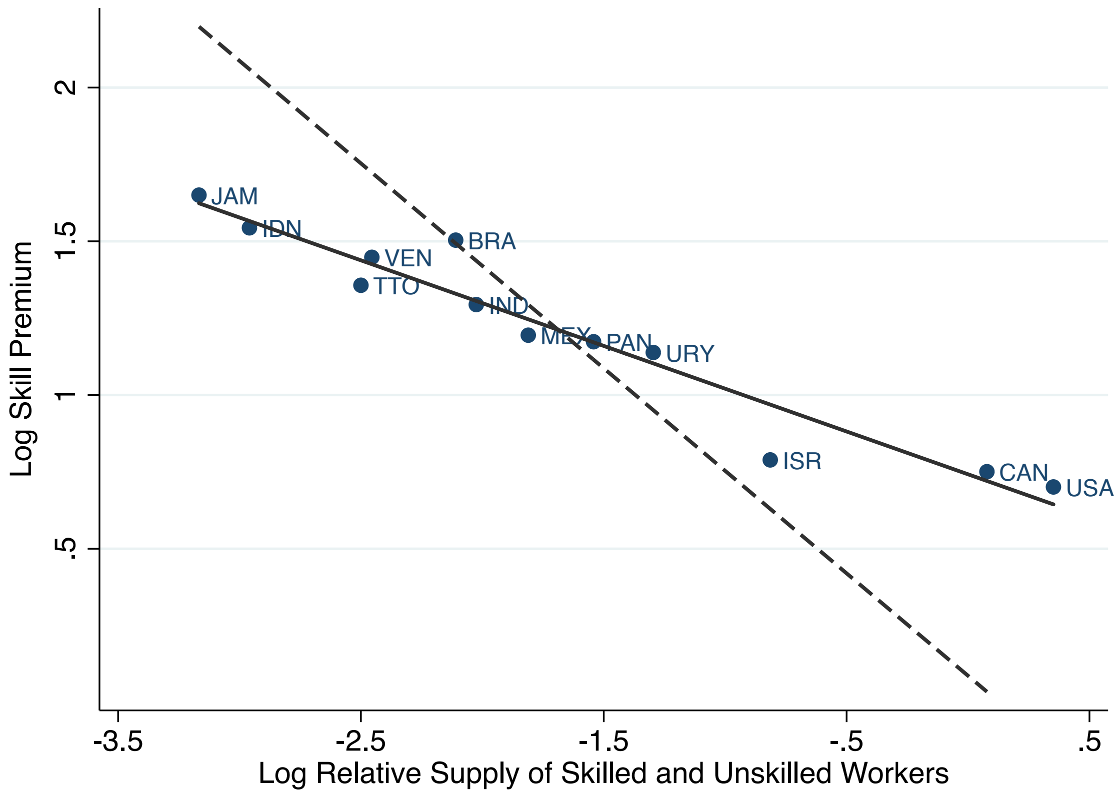
Figures

Figure I: Relative Efficiency and Relative Supply of Skilled Labor



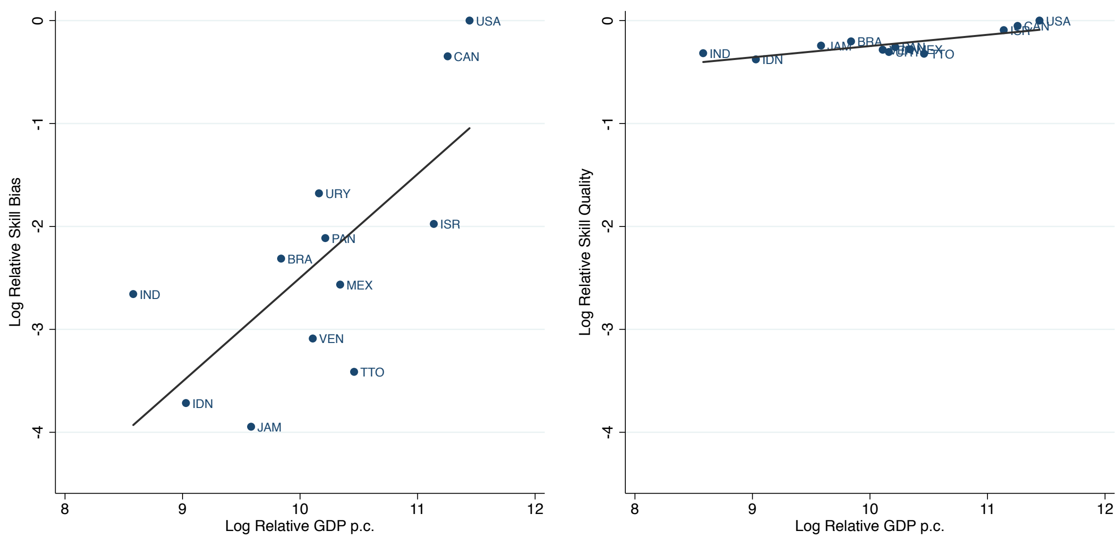
Notes: The figure plots on a log scale the relative efficiency and relative supply of skilled workers for countries in the sample. Both variables are normalized so that they take value 1 for the United States. The solid line represents the best exponential fit.

Figure II: Skill Premium and Skill Supply



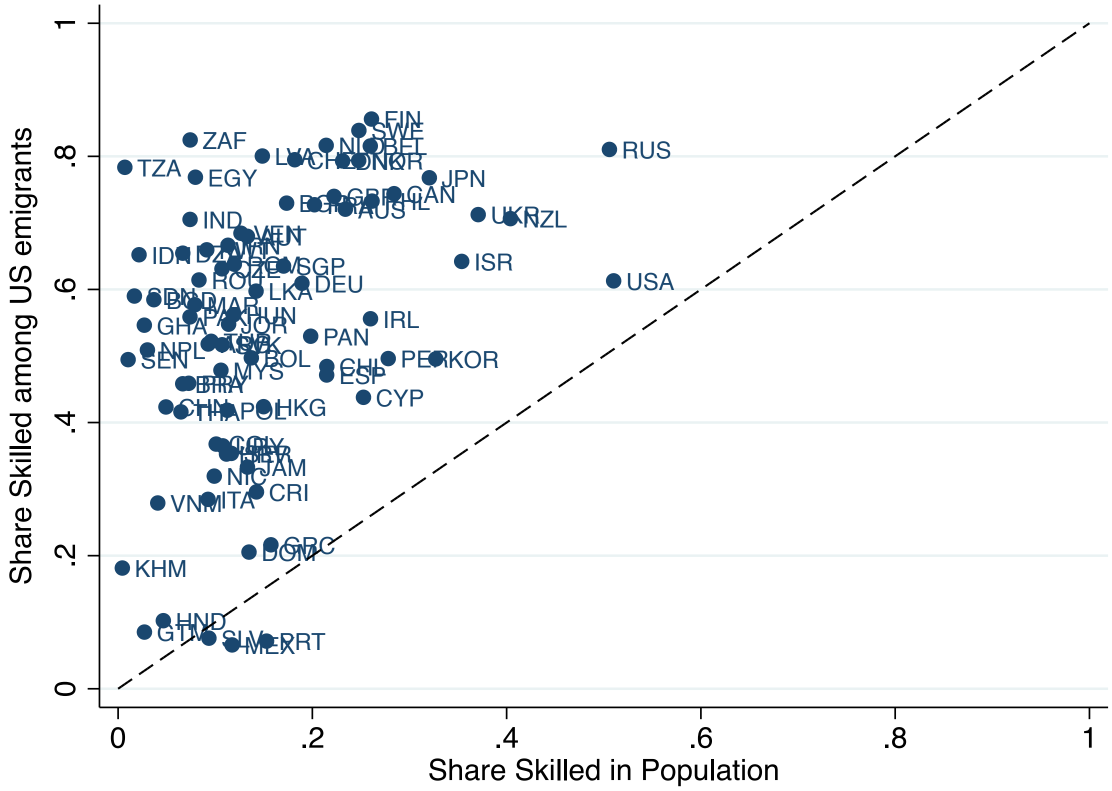
Notes: The figure plots the log skill premium and the log and relative supply of skilled workers for countries in the sample. The solid line represents the best linear fit. The dashed line has the slope of the predicted relationship (-0.67) in a counterfactual where skill efficiency and supply are uncorrelated.

Figure III: Technology Skill Bias and Skill Quality across Countries



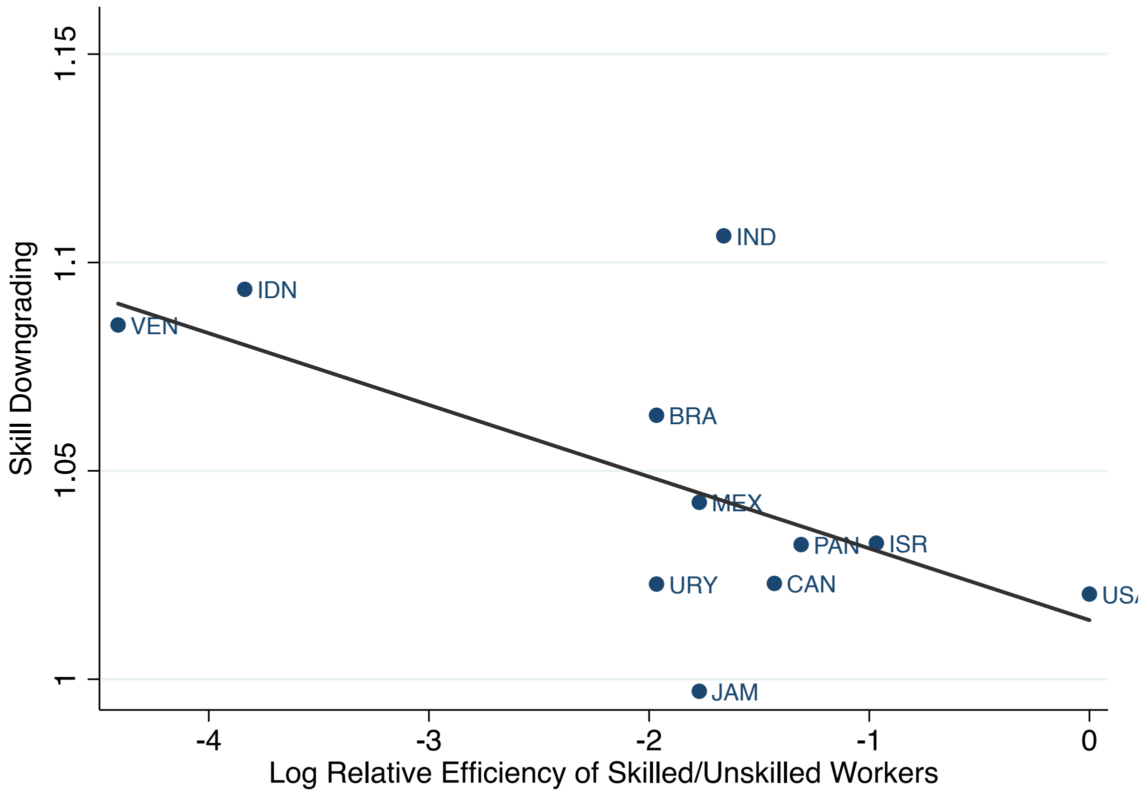
Notes: The left graph plots (on a log scale) the relative skill bias of technology against log GDP per capita. The right graph plots (on a log scale) the relative quality of skill labor against log GDP per capita. All variables are normalised such that they take value 1 for the United States. The lines show the best fits.

Figure IV: Share of Skilled Workers among Emigrants by Country of Origin



Notes: The figure plots the share of skilled workers among emigrants to the US against the one in the country of origin. Only emigrants entirely educated in their country of origin are included. Skilled workers are defined as having some tertiary education.

Figure V: Skill Downgrading and Relative Skill Efficiency



Notes: The figure plots the average migrants' skill downgrading, defined as the ratio between own years of schooling and average years of schooling among US natives employed in the same occupation, against log relative skill efficiency in the country of origin. Only skilled emigrants entirely educated in their country of origin and US natives are included in the computations. Skilled workers are defined as having completed some tertiary education. The solid line represents the best linear fit.